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Promoting enterprise productivity: The role of digital transformation

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Abstract

This study employs textual analysis to assess enterprise digitalization. Moreover, it explores the effect of firm digital transformation (DT) on productivity using data from listed enterprises in China from 2007 to 2020. Our empirical findings point to a facilitation effect between firm-level DT and productivity, which is stronger in downstream firms. Mechanism analysis shows that such increase in productivity is driven mainly by the positive effect of firm DT on technological innovation, human capital, operating capability, and investment efficiency. Further investigation reveals that promoting firm productivity through DT can boost profitability. The findings can help us better understand the economics of firm DT and therefore point to an important policy implication for increasing enterprise productivity.

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1. Introduction

With the continuous penetration of digital technology, new business opportunities, innovative products and services, and novel business models emerged and prevailed (Verhoef et al., 2021). Digital technology significantly impacts nearly all modern organizations (Bhimani, 2015). According to recent data, the average DT score of Chinese enterprises was 54 points in 2021, 50 points in 2020, 45 points in 2019, and 37 points in 2018, indicating that Chinese firm digital transformation (DT) is progressing steadily and positively (Jiang, Du, & Chen, 2022). Furthermore, since the outbreak of the COVID-19 pandemic, firms around the world have been forced to undergo transformation to survive the economic downturn (Jin et al., 2022). The severe pandemic highlighted the necessity and urgency of firm DT, forcing businesses to reconsider

DT (Jiang, Du, & Chen, 2022). In the face of profound changes in technology and the market environment in the digital age (Li et al., 2016; Verhoef et al., 2021), most companies adopted digital technologies and platforms as a strategic imperative to improve business performance and gain a sustainable competitive advantage (Verhoef et al., 2021; Vial, 2019).

The effects of DT on economic activities recently attracted widespread attention from scholars. Prior research examined the impact of digital infrastructure on economic growth from a macroscopic perspective and concluded that building digital infrastructure can significantly increase a country's economic development (e.g., Shiu & Lam, 2008). However, with the further development of the digital economy, prior literature broadened its research on digitalization to microcosmic enterprises (Jiang, Du, & Chen, 2022) and the use of microdata to provide empirical support for the positive impact of enterprise digital technology use on firm performance. By examining the relationship between firm DT and productivity, our research adds to the body of knowledge.

Although relevant studies recognized the importance of DT to firm productivity, the majority of them are based on the

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adoption of information and communication technology (Relich, 2017), data analysis (Subrahmanyam, 2019; Wu et al., 2020), broadband (Haller & Lyons, 2015), and enterprise application software (Shin, 2006), and they lack a comprehensive representation of DT. DT is a company-wide shift that propels the development of new business models (Iansiti & Lakhani, 2014; Jiang, Du, & Chen, 2022). In terms of the DT of Chinese enterprises, relevant empirical research using Chinese corporate samples remains scarce, which is not in line with the global status of China's digital economy development. In contrast to the literature, our study bridges this gap by developing a firm DT measurement, combining deep machine learning and text analysis techniques, and applying it to a sample of Chinese publicly traded corporations.

Furthermore, we draw on another body of literature that establishes a link between firm DT and firm-level characteristics associated with firm productivity, such as technological innovation (Nambisan et al., 2017), human capital (Backman, 2014; Colbert et al., 2016), operational efficiency (Porter & Heppelmann, 2014), and financial performance (Peng & Tao, 2022). Thus, we identify potential mechanisms and explicitly examine whether they influence the productivity-enhancing effect of firm DT.

Against this background, using a dataset of Chinese listed firms for the period 2007–2020, we aim to examine whether firm DT improves productivity, determine whether our main findings vary across industries, and investigate the mechanism channels between firm DT and productivity.

Our first empirical finding is that firm DT can aid in increasing productivity. Quantitatively, every one unit increase in firm DT increases productivity by 0.0066 units (we measure productivity with the total factor productivity [TFP] metric using the autocorrelation function [ACF] technique). Furthermore, the results of the heterogeneity analysis show that this promotion effect is strong in firms belonging to downstream industries. Our subsequent analyses suggest that firm DT boosts productivity by improving technological innovation, human capital, operating capability, and investment efficiency, elucidating the link between firm DT and productivity gains. Further analysis elucidates the economic impact of firm DT on productivity, that is, increasing profitability.

Our contribution is fourfold. First, we use textual analysis to assess firms' digitalization. Many studies focused on the effect of firms adopting a single digital technology, whereas our study adds robust evidence on the overall degree of firm DT and its implications for firm productivity. Second, we provide credible evidence on the relationship between DT and firm productivity in the Chinese context, which can aid in understanding whether China's digital economy development can facilitate firm performance. Employing a widely used and comparable metric, namely, TFP, we examine differences in firm productivity at various levels of DT. Third, we offer a variety of endogeneity solutions, including the instrumental method, Heckman method, propensity score matching (PSM), and placebo test method. Fourth, we meticulously identify four mechanism channels that explain how firm DT affects productivity: technological innovation, human capital,

operating capacity, and investment efficiency channels. We first identify the operating capacity channel and investment efficiency channel.

The remainder of this research proceeds as follows. Section 2 reviews previous research on firm productivity and DT and discusses our study's theoretical considerations. Section 3 describes the research variables and sample. Section 4 outlines our baseline analysis and identifies potential endogeneity issues, and Section 5 investigates the baseline relationship's heterogeneity. Section 6 examines the potential mechanism channels, and Section 7 provides further analysis. Finally, Section 8 concludes this study.

2. Literature review and theoretical development

2.1. Literature review

Firm digitalization stems mainly from three major driving forces: macroenvironment changes (Li et al., 2016; Matt et al., 2015), intensified market competition (Kohli & Melville, 2019; Mithas et al., 2013), and consumer behavior changes (Abrell et al., 2016; Verhoef et al., 2021). DT refers to the innovation process through which companies use digital technologies (Hess et al., 2016). By changing operating strategies, processes, products, services, organizations, and supply chains of enterprises, companies are able to adapt to the highly variable digital environment, achieve significant business improvements, enhance customer experience, streamline their operating style, and create new business models all through DT (Warner & Wäger, 2019).

Two strands are primarily the focus of the literature on DT. The first strand concerns the link between DT and firm performance, including increased sales revenue (Brock and Von, 2019), improved operational efficiency (Bhimani, 2015; Svahn et al., 2017), cost reduction (Pagani, 2013), innovation (Cuevas-Vargas et al., 2022; Usai et al., 2021), financial performance (Peng & Tao, 2022), and competitive advantages (Björkdahl, 2020). The second strand focuses on identifying elements that enable firms to reap the potential benefits anticipated from DT, such as digital culture (Guy, 2019; Martínez-Caro et al., 2020; Roth, 2019), digital workforce (Baptista et al., 2017; Colbert et al., 2016), digital awareness (Hanelt et al., 2021; Singh et al., 2020), digital agility (Li et al., 2016; Lu & Ramamurthy, 2011), organizational structure (Eggers & Park, 2018; Verhoef et al., 2021), and digital platform (Markus & Loebbecke, 2013).

As previously discussed, the application of digital technology can demonstrate a profound impact on firms' organizational logic and innovation (Yoo, 2010), allowing them to generate novel products and services, commercial models, operating strategies, and organizational structures in novel ways (Jiang, Du, & Chen, 2022; Verhoef et al., 2021; Warner & Wäger, 2019). Corporations' efficiency in cost management, resource allocation, and external environment monitoring notably improved due to DT, thus increasing firm productivity (Björkdahl, 2020; Porter & Heppelmann, 2014). Previous research established a link between DT and firm productivity.

For instance, based on previous case studies, [Shin \(2006\)](#) adopted formal econometric methods to demonstrate further that firm-level software applications can significantly increase the productivity of Korean small- and medium-sized enterprises. [Pan et al. \(2015\)](#) validated enterprises' processes of improving productivity by employing IT technology through a case study of Batamindo Shipping & Warehouse Pte., Ltd. Meanwhile, [Wu et al. \(2020\)](#) believed that a complementary relationship exists between data analytics, innovation, and firm productivity based on empirical results from mixed data sources such as survey data from 331 large firms, patent data, and large-scale résumé data.

However, previous studies that examined the importance of firm DT to productivity mostly summarized their findings from case studies or empirical results from survey data and lacked formal econometric approaches. Furthermore, the literature focuses on the effects of single digital technology applications on operating results from both macro and micro perspectives (e.g., [Relich, 2017](#); [Shin, 2006](#)), but evidence from comprehensive indicators of firm DT and Chinese firms is limited. As digital technologies become more widely adopted, the benefits of firm DT are likely to vary considerably across firms. Thus, the overall enterprise transformation in China and its implications for firm productivity must be further analyzed. Additionally, studies on how firm DT improves productivity are insufficient, thereby motivating us to clarify potential mediating mechanisms between the two factors to complement the literature.

2.2. Theoretical considerations

This paper evaluates the positive effects of DT on firm productivity. We contend that four potential channels are associated with DT and productivity in organizations.

First, technological innovation is a key driver of productivity growth ([Fang et al., 2020](#); [Yu & Fu, 2021](#)). Numerous studies demonstrated that firm DT is crucial to technological innovation (e.g., [Ardito et al., 2018](#); [Nambisan et al., 2017](#)). On the one hand, owing to the unique characteristics of digital technologies ([Hinings et al., 2018](#)), firms are able to foster technological innovation ([Nambisan et al., 2017](#)). On the other hand, DT enhanced the capacity of firms to mine and integrate internal and external information and fostered their high agility for forward-looking technologies ([Sambamurthy et al., 2003](#)), which is conducive to understanding the direction of technological innovation and enhancing innovation. Specifically, going digital can assist businesses in enhancing their data analysis capacity and inducing process and diverse recombination innovations ([Wu et al., 2020](#)). Accordingly, we argue that firm DT can facilitate productivity gains by fostering technological innovation.

Second, DT can increase firm productivity by enhancing the intelligence of business models through the application of digital technologies, optimized inventory management, business analysis, and business production and operation process upgrades. During this process, the traditional workforce will be eliminated, but highly educated or skilled employees will

survive due to their propensity for adopting DT. Following the “survival of the fittest,” firm-specific human capital can be enhanced. Moreover, firm-specific human capital boosts enterprise productivity (e.g., [Backman, 2014](#); [Kim & Ployhart, 2014](#); [Oppong & Pattanayak, 2019](#)). The close relationship between human capital and innovation ([He et al., 2022](#); [Kianto et al., 2017](#)) suggests that highly educated or skilled personnel can assist firms in achieving high productivity in digitalization.

Third, operating capacity refers to a company's ability to allocate resources efficiently and rationally utilize assets, reflecting the company's competitiveness and influencing firm productivity ([Xiao et al., 2021](#)). In addition, satisfactory operating capacity denotes an enhanced financial position, thereby inducing high productivity ([Li et al., 2018](#)). The literature review led us to conjecture that DT exerts a positive impact on operational efficiency. Thus, we believe that the increased availability of and reliance on big data analysis and cloud computing services provide firms with the opportunity to increase their operational capacity. In addition, going digital may spur the development of optimal organizational structures, processes, and business models, which may result in improved operating capacity ([Verhoef et al., 2021](#)).

Finally, scholars asserted that DT can help generate sustainable competitive advantages ([Björkdahl, 2020](#); [Martínez-Caro et al., 2020](#); [Warner & Wäger, 2019](#)), which may result in a significant positive effect on investment efficiency. The improvement in information management brought about by DT can assist firms in identifying investment opportunities while preventing them from making irrational investment decisions, thereby improving their investment efficiency. Furthermore, DT can improve financial performance ([Peng & Tao, 2022](#)), which is a significant factor affecting the investment efficiency of corporations (e.g., [Biddle et al., 2009](#); [Chen, Hope, et al., 2011](#); [Chen, Sun, et al., 2011](#); [Hu et al., 2019](#)). Because investment efficiency is the primary determinant of firm-level productivity, we hypothesize that firm DT can increase productivity by fostering investment efficiency.

In summary, we argue that DT may contribute to firm productivity gains, with technological innovation, human capital, operating capability, and investment efficiency providing the theoretical justification for this impact. Section 5 examines the aforementioned potential channels.

3. Variable measurements and data

3.1. Firm productivity

Regarding the firm productivity measurement, the literature typically employed TFP, that is, the Solow residual first proposed by [Solow \(1956\)](#). The most popular measurement methods for TFP are parametric approaches, such as ordinary least squares (OLS), and semiparametric methods, such as the method of [Olley and Pakes \(1996\)](#), [Levinsohn and Petrin \(2003\)](#), and ACF. To calculate the residuals, the OLS method uses the linear estimation in order to determine a firm's TFP under the presumption that economic activities follow a particular production function. Meanwhile, the OP method uses

investment expenditure as a proxy variable for the productivity shock, which helps address simultaneity and selection bias (Olley & Pakes, 1996). However, enterprises without investment expenditures are excluded from the regression, and the TFP value calculated using the OP approach contains missing values (Levinsohn & Petrin, 2003). To mitigate sample losses in the face of such issues, Levinsohn and Petrin (2003) employed intermediate inputs as the proxy variable. Meanwhile, the labor coefficient may experience multicollinearity and identification problems in the first stage estimation. Akerberg et al. (2015) proposed an alternative strategy incorporating the labor input into the intermediate input function and developed the ACF method, thereby improving the accuracy of TFP estimation.

The ACF technique is the main method we use for our analysis, which is consistent with the most recent empirical studies on productivity in China (Yu & Qi, 2021; Zhang et al., 2021). Following Akerberg et al. (2015), we present the details of our ACF-based estimation of firms' TFP. In addition, to estimate the firms' TFP, we use the OLS and LP techniques in the robustness tests.

The natural logarithmic form of the Cobb–Douglas production function is as follows:

$$y_{i,t} = \alpha_0 + \alpha_L l_{i,t} + \alpha_K k_{i,t} + \alpha_M m_{i,t} + \varepsilon_{i,t} \quad (1)$$

where $y_{i,t}$ denotes the natural log of the value added of firm i in year t , $l_{i,t}$ represents the natural logarithm of the input in labor, $k_{i,t}$ refers to the natural logarithm of the labor in capital, $m_{i,t}$ is the natural log of the intermediate input, α_0 represents the average level of efficiency across firms over a period, and $\varepsilon_{i,t}$ represents the year- and corporate-specific deviation from the mean. We can decompose $\varepsilon_{i,t}$ into predictable and unpredictable shocks to production or productivity. Then, Eq. (1) can be translated into the following:

$$y_{i,t} = \alpha_0 + \alpha_L l_{i,t} + \alpha_K k_{i,t} + \alpha_M m_{i,t} + \nu_{i,t} + u_{i,t} \quad (2)$$

where $u_{i,t}$ represents unobservable (or unpredictable) productivity shocks or the measurement error. We define $\omega_{i,t} = \alpha_0 + \nu_{i,t}$ based on the assumption that $\omega_{i,t}$ refers to a state variable in the enterprise's decision problem, that is, a determinant of enterprise selection and input demand decision (Olley & Pakes, 1996). In addition, $\omega_{i,t}$ represents firm-level productivity, which is our topic of interest.

Typically, the empirical literature solved for $\omega_{i,t}$ by estimating Eq. (2). Next, we measure the estimated firm-level productivity as follows:

$$\hat{\omega}_{i,t} = \alpha_0 + \nu_{i,t} = y_{i,t} - \alpha_L l_{i,t} - \alpha_K k_{i,t} - \alpha_M m_{i,t} - u_{i,t} \quad (3)$$

The ACF method formulates the demand function of a firm's intermediate input as $m_{i,t} = f(l_{i,t}, k_{i,t}, \omega_{i,t})$. We invert the intermediate input $\omega_{i,t} = f^{(-1)}(l_{i,t}, k_{i,t}, m_{i,t})$ and substitute it into Eq. (3):

$$\begin{aligned} \hat{\omega}_{i,t} &= f^{(-1)}(l_{i,t}, k_{i,t}, m_{i,t}) = \phi(l_{i,t}, k_{i,t}, m_{i,t}) \\ &= y_{i,t} - \alpha_L l_{i,t} - \alpha_K k_{i,t} - \alpha_M m_{i,t} - u_{i,t} \end{aligned} \quad (4)$$

where $f^{(-1)}(\cdot)$ and $\phi(\cdot)$ are functions with a polynomial in the logarithm of the input in labor, natural logarithm of the input in capital, and natural logarithm of the intermediate input.

With the regression function of Eq. (4), the OP and LP methods employ two-stage algorithms to estimate the coefficients of $l_{i,t}$ in the first stage and the coefficients of $k_{i,t}$ and $m_{i,t}$ in the second stage. Following the ACF method, we estimate the coefficients of $l_{i,t}$, $k_{i,t}$, and $m_{i,t}$ in the second stage, but we eliminate only the interference of the error components in the production function in the first stage (Van Beveren, 2012).

ACF assumes that (1) $E[u_{i,t}|I_{i,t}] = E[y_{i,t} - \phi(l_{i,t}, k_{i,t}, m_{i,t})] = 0$, and $I_{i,t}$ is the information set of firm i in year t . (2) Eq. (4) is performed through the OLS regression of $y_{i,t}$ on a high-order polynomial in $(l_{i,t}, k_{i,t}, m_{i,t})$, so we can obtain an unbiased estimator of $\phi(l_{i,t}, k_{i,t}, m_{i,t})$, denoted as $\hat{\phi}(l_{i,t}, k_{i,t}, m_{i,t})$. (3) $\omega_{i,t}$ follows a first-order Markov process, which can be written as $\omega_{i,t} = g(\omega_{i,t-1}) + \zeta_{i,t}$, where $g(\cdot)$ is a function with a low-degree polynomial in the dependent variables, and $\zeta_{i,t}$ represents innovation in the productivity of firm i in year t . (4) The capital input is decided in year $t-1$, which means that the productivity shock in year t may not affect the capital input in year t but may affect the labor input, which is more flexible. With these assumptions, we can obtain $\hat{\omega}_{i,t}$, as follows:

$$\hat{\omega}_{i,t} = f^{(-1)}(l_{i,t}, k_{i,t}, m_{i,t}) = \hat{\phi}(l_{i,t}, k_{i,t}, m_{i,t}) - \alpha_L l_{i,t} - \alpha_K k_{i,t} - \alpha_M m_{i,t} \quad (5)$$

and

$$\begin{aligned} \zeta_{i,t} &= \hat{\omega}_{i,t} - g(\omega_{i,t-1}) = \hat{\phi}(l_{i,t}, k_{i,t}, m_{i,t}) - \alpha_L l_{i,t} - \alpha_K k_{i,t} - \alpha_M m_{i,t} \\ &\quad - g(\hat{\phi}(l_{i,t-1}, k_{i,t-1}, m_{i,t-1}) - \alpha_L l_{i,t-1} - \alpha_K k_{i,t-1} - \alpha_M m_{i,t-1}) \end{aligned} \quad (6)$$

and the moment condition

$$E[\zeta_{i,t}|k_{i,t}] = 0; E[\zeta_{i,t}|I_{i,t-1}] = 0 \quad (7)$$

3.2. DT

Next, to construct a comprehensive indicator of DT within firms, we use a combination of advanced machine learning and text analysis. Specifically, the indicator construction process is fourfold. First, we compile the annual MD&As of all Chinese publicly traded companies for the period of 2007–2020. After the extraction and manual screening, 37,266 MD&As are obtained. Second, we refer to key and recent Chinese policy documents, such as the “Special Action Plan for Digital Empowerment of Small and Medium-Sized Enterprises,” the “Notice on Accelerating the Digital Transformation of State-Owned Enterprises,” “Made in China 2025,” and Chapter 5 of “China's 14th Five-Year Plan.” Next, we acquire a dictionary of digital technology-related keywords, such as big data, AI, cloud computing, VR, blockchain, the IoT, 5G, the industrial Internet, and DevOps. As the DT of business models

also represents firm DT (Verhoef et al., 2021), we further categorize keywords associated with the DT of business models. Therefore, we expand upon the fundamental phrases from three perspectives: intelligent manufacturing, digital marketing, and digital management. Our standard phrases for firm DT are reasonable and exhaustive. Third, given the variety of Chinese-language expressions, to determine the keywords that are semantically related to our basic phrases, we employ the RoBERTa-wwm-ext deep machine learning model. Then, we retain the extended phrases with a cosine similarity of greater than 0.80 with our basic phrases. Subsequently, we eliminate the phrases unrelated to enterprise DT and construct a dictionary of 86 Chinese keywords for firm DT. Finally, we employ text analysis to count the number of occurrences of the Chinese keywords from our dictionary across all the MD&As and establish the natural logarithm of the keywords' frequency as a proxy variable for the firm's DT, denoted as *DT*. For the firms that disclose intangible asset items in detail, following Jiang, Du, and Chen (2022), we compute the proportion of digital intangible assets associated with DT keywords in the intangible assets, denoted as *DA*. Furthermore, we calculate the natural logarithm of the term count frequency of digital technology application keywords (denoted as *DigiTech*) and the natural logarithm of the term count frequency of the business model transformation keywords (denoted as *DB*).

3.3. Control variables

Following the literature (Demir et al., 2022; Kong et al., 2020), we include control variables that may affect firm productivity, including *asset*, which is the natural log of the total asset; *age*, which is the natural log of the established age; *leverage*, which is the ratio of total liabilities to total assets and represents a firm's access to credit, demonstrated to affect firm productivity growth (Li et al., 2018); and *roe*, which represents return on equity. Also, we control for a firm's tax rate (denoted as *tax*), as the burden of taxes on a firm may affect its output (Peng et al., 2021; Yu & Qi, 2021). The operating income growth over the previous year, denoted as *growth*, is how we gauge a company's growth rate.

Motivated by Tian and Twite (2011), we further control for a set of variables reflecting corporate governance, namely, *director*, which is the logarithm of the number of directors; *opinion*, a dummy variable that takes 1 if a firm's audit comment is standard and qualified, and 0 otherwise; *duality*, a dummy variable that is equal to 1 if the CEO is also the chairman of the board, and 0 otherwise; and *outdirrate*, which is the proportion of outside directors on the board. Prior research largely supported the heterogeneous productivity effects between state-owned enterprises (SOEs) and non-SOEs (e.g., Li et al., 2018; Peng et al., 2021). Low productivity in SOEs may be a result of problems like subpar financial performance (Li et al., 2018), high agency costs (Mi & Wang, 2000), and a lack of competitive pressure (Jefferson et al., 2000). Therefore, we further control for *state*, a dummy variable that is equal to 1 if it is an SOE, and 0 otherwise. Table A1 lists the definitions of the variables.

3.4. Data

To disentangle the effects of enterprise digitalization on productivity, we collect data from various sources. Because the information disclosure system for listed companies was improved in 2007, we begin our empirical investigation with a panel dataset of Chinese listed companies for the period 2007–2020. Our primary firm-level data are obtained from the CSMAR and Wind databases. The annual reports of the listed firms used to measure firm DT are from two Chinese stock exchanges. Referring to existing literature (e.g., Zhou et al., 2022), we exclude firms in the financial industry owing to their different debt structure. Also, we exclude delisted firms, firms marked with *ST or ST, firms that issue A- and B-shares, and samples from the IPO year and earlier. Our regression sample includes 29,408 enterprise-year observations. Table 1 displays the variable data statistics.

4. Baseline analysis

4.1. Econometric methodology

Our main research question is whether firm DT affects productivity. Therefore, we construct the following regression for our baseline analysis.

$$TFP_acf_{i,t} = \beta_0 + \beta_1 DT_{i,t} + \gamma CVs_{i,t} + \lambda_t + \eta_j + \varepsilon_{i,t} \quad (8)$$

where *i* and *t* represent the firm and year, respectively. The dependent variable in this study is *TFP_acf_{i,t}*, referring to the productivity of firm *i* in year *t*. The independent variable is *DT_{i,t}*, which represents the overall degree of the digitalization level of enterprise *i* at year *t*. *CVs_{i,t}* are the control variables, λ_t represents the year fixed effects, η_j represents the industry fixed effects, and $\varepsilon_{i,t}$ is the error term.

4.2. Baseline empirical results

Table 2 displays the baseline findings. We do not include any control variables in the regression in Column (1). The *DT* coefficient is statistically significant and positive, indicating that firm DT can promote productivity. We get a similar result when we exclude the year fixed effects and the industry fixed effects in Column (2). Column (3) displays the results of the model (8), and the coefficient of *DT* is positive and significant at the 1% level. In addition, the absolute value of $\hat{\beta}_1$ is 0.0066, thereby implying that for every one unit increase in enterprise digitalization, enterprise productivity will be improved by 0.0066 units. The absolute value of $\hat{\beta}_1$ in Column (3) is smaller than that in Columns (1) and (2), thereby suggesting that the control variables and fixed effects in Eq. (8) mitigate the interference of confounders on the causal effect estimates.

Regarding the control variables, regression results show that enterprise productivity is positively related to its size (denoted as *asset*), return on equity (denoted as *roe*), and revenue growth (denoted as *growth*). In contrast, it is negatively related to its ratio of total liabilities to all assets (denoted as *leverage*). Further, our findings are consistent with previous studies that

Table 1
Descriptive statistics.

Variable	N	Mean	SD	Min	P25	P50	P75	Max
<i>TFP_acf</i>	29,408	0.815	0.236	0.344	0.667	0.774	0.915	1.708
<i>DT</i>	29,408	2.043	1.596	0	0.693	1.946	3.219	5.784
<i>asset</i>	29,408	22.12	1.273	19.78	21.21	21.94	22.83	26.14
<i>age</i>	29,394	2.744	0.390	1.386	2.485	2.773	3.045	3.434
<i>leverage</i>	29,408	0.439	0.205	0.056	0.277	0.435	0.593	0.898
<i>roe</i>	29,340	0.053	0.150	−0.899	0.028	0.068	0.114	0.314
<i>tax</i>	29,408	0.035	0.041	−0.018	0.011	0.022	0.041	0.227
<i>growth</i>	29,374	0.425	1.198	−0.716	−0.030	0.138	0.431	8.833
<i>director</i>	29,329	2.139	0.201	1.609	1.946	2.197	2.197	2.708
<i>opinion</i>	29,408	0.967	0.178	0	1	1	1	1
<i>duality</i>	29,408	0.251	0.433	0	0	0	1	1
<i>outdirrate</i>	29,329	0.374	0.053	0.312	0.333	0.333	0.429	0.571
<i>state</i>	29,360	0.403	0.490	0	0	0	1	1
<i>TFP_lp</i>	29,408	9.049	1.102	6.737	8.288	8.944	9.704	12.04
<i>TFP_ols</i>	29,408	10.94	1.272	8.285	10.06	10.81	11.70	14.42
<i>DA</i>	17,878	0.003	0.008	−0.001	0.000	0.001	0.002	0.227
<i>DigiTech</i>	29,408	1.140	1.467	0	0	0	1.946	5.278
<i>DB</i>	29,408	1.689	1.391	0	0	1.609	2.708	5.130
<i>DR</i>	29,408	2.406	1.170	1	1	2	3	4

Table 2
Baseline results of digital transformation and firm productivity.

	(1)	(2)	(3)
	<i>TFP_acf</i>	<i>TFP_acf</i>	<i>TFP_acf</i>
<i>DT</i>	0.0117*** (5.9792)	0.0353*** (21.814)	0.0066*** (4.1187)
<i>asset</i>		0.0184*** (7.2543)	0.0086*** (3.5808)
<i>age</i>		0.0219*** (3.6402)	−0.0220*** (−3.3828)
<i>leverage</i>		−0.2486*** (−16.063)	−0.2256*** (−16.950)
<i>roe</i>		0.2931*** (20.127)	0.3411*** (24.981)
<i>tax</i>		2.5950*** (25.181)	2.4189*** (19.901)
<i>growth</i>		0.0078*** (4.4498)	0.0041** (2.5725)
<i>director</i>		−0.0324** (−2.1225)	−0.0110 (−0.8400)
<i>opinion</i>		−0.0327*** (−2.9484)	−0.0119 (−1.1536)
<i>duality</i>		0.0159*** (3.2697)	0.0131*** (3.2197)
<i>outdirrate</i>		−0.0057 (−0.1212)	−0.0015 (−0.0368)
<i>state</i>		0.0096 (1.5810)	0.0004 (0.0661)
<i>Constant</i>	0.7915*** (153.61)	0.3722*** (5.9370)	0.7006*** (11.756)
Industry FE	Y	No	Y
Year FE	Y	No	Y
Firm cluster	Y	Y	Y
R2	0.2866	0.3929	0.5237
N	29,407	29,182	29,181

Note: parentheses report t-statistic; we employ ***, **, and * to represent the statistical significance level at 1%, 5%, and 10%, respectively. We controlled fixed effects in all columns at the year and industry-level. In every regression, this paper clustered standard errors at the corporate level. For the definitions of all the variables, see Table A1.

investigated the productivity of listed firms in China (Demir et al., 2022; Kong et al., 2020), indicating that our methodology is sound. Surprisingly, we discover that enterprise productivity is negatively related to age but positively related to tax rate (denoted as *tax*) and the dummy variable for duality (denoted as *duality*), which can be explained by taking into account the Chinese context. First, young firms demonstrate high levels of innovation (Fang et al., 2020; Howell, 2017), considerable growth opportunities (Cull et al., 2015), and few government inventions, allowing them to achieve high levels of productivity. Second, SOEs, zombie firms, and companies operating in the red benefit from tax breaks in China but exhibit low productivity (Li et al., 2018; Shen & Chen, 2017), which can partly explain the sign of our tax coefficient. Third, the unification of the CEO and chairman can issue clear instructions to subordinates, making enterprise decision-making highly effective and resulting in increased enterprise productivity (Chiang & Lin, 2007). Furthermore, to save on human resource costs, duality is most common in young and small enterprises, which tend to be highly productive.

4.3. Endogeneity

Although fixed effects panel regressions partially address endogeneity concerns when analyzing the relationship between firm DT and productivity, endogeneity issues may still exist in the model (8). We employ the instrumental 2SLS method, PSM, the Heckman method, and placebo test to examine the potential endogeneity of firm DT. After adjusting for potential endogeneity issues, we can conclude that DT promotes firm productivity.

4.3.1. Instrumental variable method

A qualified instrumental variable satisfies two types of restrictions, namely an exclusion restriction and a relevance restriction (Demir et al., 2022). Therefore, in this section, we

include the average value of the digitalization level of other enterprises in the same industry as an instrument, denoted as IV . We assert that IV meets both the exclusion and relevance assumptions. Firm i 's productivity may not be directly affected by the digitalization of other firms in the same industry; thus, IV satisfies the exclusion assumption. In addition, firms within the same industry share similar industry characteristics and market environments; consequently, their DT decisions are relevant. In the initial stage of regression, the relevance assumption can be examined. On the basis of the aforementioned argument, we conclude that our instrument for DT is qualified.

Table 3 displays the pertinent findings. The results of the first stage regression are shown in Column (1). Our assumption that our instrument is applicable to firm DT is supported by the estimated coefficient of IV , which is significantly positive at the 1% level. The outcomes of the second stage regression are shown in Column (2). The coefficient of DT is still significantly positive, supporting our initial finding. Meanwhile, the Kleibergen–Paap rk LM statistic is 95.080, and the corresponding p-value is 0.000, thereby passing the under-identification test. In addition, the Kleibergen–Paap Wald rk F-statistic is 202.088, and the Cragg–Donald Wald F-statistic is 102.470, which excludes weak instrumental variables. Additionally, we notice that $\hat{\beta}_1$ in Table 3 is greater than it was in the baseline regression, suggesting that the instrumental variable method reduces the bias caused by endogenous problems.

The average value of other firms' DT s within the same sector illustrates how industry factors affect firm productivity. Therefore, we add two industry-level control variables: SD_TFP and HHI . Specifically, SD_TFP represents the degree of resource misallocation of a specific industry and is calculated by the standard deviation of a firm's productivity

in the industry (Hsieh & Klenow, 2009; Zheng et al., 2021). Meanwhile, HHI represents the industry-level Herfindahl–Hirschman index. Referring to Tian and Twite (2011), we calculate the Herfindahl–Hirschman index of each two-digit industry using firm assets, as follows:

$$HHI_{j,t} = \sum_i \left(\frac{asset_{i,j,t}}{\sum_i asset_{i,j,t}} \right)^2 \quad (9)$$

where i, j , and t represent enterprise, industry, and year indices, respectively; $HHI_{j,t}$ represents the Herfindahl index of industry j in year t ; and $asset_{i,j,t}$ refers to the total assets of firm i in industry j in year t . Columns (3) and (4) show the results of the first and second stages of instrumental variable regression, after we control for industry factors. Next, we discover that the DT coefficient remains positive. The Kleibergen–Paap rk LM statistic is 95.326, with a p-value of 0.000, passing the under-identification test. Moreover, the Kleibergen–Paap Wald rk F-statistic is 201.950, and the Cragg–Donald Wald F-statistic is 102.713, which excludes weak instrumental variables. In summary, the aforementioned findings validate the robustness of our baseline conclusion.

A common method is to construct instrumental variables using exogenous policies (Duong et al., 2020). Thus, we establish a new instrumental variable, namely, $BroadBand_{c,t}$, taking the value of 1 if city c suffers from the Broadband China policy shock in year t , and 0 otherwise. We believe that $BroadBand$ is a qualified instrumental variable. The Chinese government launched the Broadband China pilot policy in 2012, and relevant government departments selected 120 cities as experiment cities for broadband construction in 2014, 2015, and 2016 (Jiang, Chen, et al., 2022). We anticipate that the Broadband China policy will result in a positive impact on the DT of local firms in the experiment regions due to improvements in telecommunications infrastructure and information technology (Brynjolfsson & Hitt, 2000). Therefore, $BroadBand$ satisfies the relevant condition, which we investigate in the first stage of regression. Furthermore, the Broadband China pilot policy is unexpected and exogenous, satisfying the exclusion condition.

Table 4 displays the relevant results. Column (1) shows the estimated results of the IV first stage regression. The coefficient of $BroadBand$ is 0.1589 at the 1% level significance level, supporting our relevance assumption. Column (2) displays the outcomes of the second stage regression. The DT coefficient remains positive and significant at the 1% statistical level, confirming our initial conclusion. The under-identification test is passed because the Kleibergen–Paap rk LM statistic is 20.770, and the corresponding p-value is 0.000. Moreover, the Kleibergen–Paap Wald rk F-statistic is 87.502, and the Cragg–Donald Wald F-statistic is 20.842, which excludes weak instrumental variables. Furthermore, we notice that $\hat{\beta}_1$ in Table 4 is larger than that in the baseline regression, implying that our instrumental variable method reduces the bias caused by endogenous issues.

Because the Broadband China pilot policy is aimed at Chinese cities, we supplement our instrumental variable analysis with some region-level controls. Specifically, we include $EL_{i,c}$,

Table 3
Endogeneity: instrumental variable regression I.

	(1)	(2)	(3)	(4)
	DT	TFP_acf	DT	TFP_acf
DT		0.0486*** (2.6092)		0.0505*** (2.8454)
IV	0.3668*** (10.1227)		0.3668*** (10.1348)	
SD_TFP			0.0713 (0.3177)	0.4523*** (8.2784)
HHI			−0.0527 (−0.3142)	−0.1523*** (−4.6044)
Industry FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Firm cluster	Y	Y	Y	Y
CVs	Y	Y	Y	Y
LM statistic	95.080	95.326		
CDF	202.088	201.950		
KPF	102.470	102.713		
N	29,105	29,105	29,105	29,105

Note: parentheses report t-statistic; we employ ***, **, and * to represent the statistical significance level at 1%, 5%, and 10%, respectively. We controlled fixed effects in all columns at the year and industry-level. In every regression, this paper added all control variables, and clustered standard errors at the corporate level. LM statistic is the Kleibergen–Paap rk LM statistic; CDF is the Cragg–Donald Wald F-statistic; KPF is the Kleibergen–Paap Wald rk F-statistic. For the definitions of all the variables, see Table A1.

Table 4
Endogeneity: instrumental variable regression II

	(1)	(2)	(3)	(4)
	<i>DT</i>	<i>TFP_acf</i>	<i>DT</i>	<i>TFP_acf</i>
<i>DT</i>		0.1115*** (3.0357)		0.0833** (2.2171)
<i>BroadBand</i>	0.1589*** (4.5653)		0.1594*** (4.1662)	
<i>EL</i>			0.0013 (0.5765)	−0.0004 (−1.1448)
<i>GL</i>			5.4572 (1.1623)	2.1170** (2.3955)
<i>OL</i>			−0.0101 (−0.0524)	0.0267 (0.7185)
Industry FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Firm cluster	Y	Y	Y	Y
CVs	Y	Y	Y	Y
LM statistic	20.770	17.323		
CDF	87.502	52.720		
KPF	20.842	17.357		
R2	0.5633	0.0259	0.5633	0.1736
N	29,181	29,181	20,091	20,091

Note: parentheses report t-statistic; we employ ***, **, and * to represent the statistical significance level at 1%, 5%, and 10%, respectively. We controlled fixed effects in all columns at the year and industry-level. In every regression, this paper added all control variables, and clustered standard errors at the corporate level. LM statistic is the Kleibergen–Paap rk LM statistic; CDF is the Cragg–Donald Wald F-statistic; KPF is the Kleibergen–Paap Wald rk F-statistic. For the definitions of all the variables, see Table A1.

which represents the level of economic development of city c and is measured as the GDP growth rate; $GL_{i,c}$, which represents the level of government invention of city c and is calculated as the expenditure in the general budget of the local government divided by the GDP; and $OL_{i,c}$, which represents the level of openness of city c and is calculated as the actual use of foreign capital divided by the GDP. Columns (3)–(4) of Table 4 show the relevant results. We find that the coefficients of *BroadBand* in Column (3) in the first stage and *DT* in Column (4) in the second stage remain positive and significant. The Kleibergen–Paap rk LM statistic is 17.323, with a p-value of 0.000, passing the under-identification test. The Kleibergen–Paap Wald rk F-statistic is 52.720, whereas the Cragg–Donald Wald F-statistic is 17.357, which excludes weak instrumental variables. $\hat{\beta}_1$ in Column (4) remains greater than the value in the baseline regression. The preceding results demonstrate that our benchmark conclusion has been established.

4.3.2. Heckman two-step method

Sample selection bias may exist in Eq. (10); hence, to reduce the possibility of an endogenous problem, we utilize the Heckman two-step method (Hill et al., 2021). Specifically, first, we use the following equation for probit regression to calculate the inverse Mills ratio, represented by *IMR*:

$$Heckman_dummy_{i,t} = \alpha + \beta CV_{s,i,t} + \lambda_t + \eta_j + \varepsilon_{i,t} \quad (10)$$

where *Heckman_dummy_{i,t}* is a dummy variable taking 1 if firm i 's *DT* is higher than the average, and 0 otherwise; *CVs* refers

to a vector of the control variables, which is consistent with Eq. (8); λ_t is the year fixed effects; η_j is the industry fixed effects; and $\varepsilon_{i,t}$ is the error term.

In the second stage, we control for *IMR* in addition to the other variables in Eq. (8). The results are presented in Column (1) of Table 5. We find that $\hat{\beta}_1$ remains positive at the 1% statistical significance level, indicating that our benchmark conclusion is robust in the face of sample selection bias. In addition, the coefficient of *IMR* is positive, supporting our hypothesis that sample selection bias exists in Eq. (8).

4.3.3. Propensity score matching

To alleviate endogeneity concerns regarding self-selection bias in the regression, we use PSM to distinguish between the treatment effect and selection effect of *DT* on firm productivity based on observable characteristics. We employ 1:2 nearest-neighbor matching based on the following logit regression:

$$PSM_dummy_{i,t} = \alpha + \beta CV_{s,i,t} + \lambda_t + \eta_j + \varepsilon_{i,t} \quad (11)$$

where *PSM_dummy_{i,t}* is a dummy variable that takes the value of 1 if firm i 's average level of *DT* in year t is higher than the 80% quantile, and 0 otherwise. The other variables in Eq. (11) are consistent with those in Eq. (8).

Using the propensity scores from the pre-match regression and nearest-neighbor 1:2 matching, the treated firms with a high level of *DT* are matched with the control firms with a low level of *DT*. Table A2 details the PSM's balance test. We observe few notable differences between the control and treated enterprises. Fig. 1 depicts the core density curves of the propensity scores of the control firms and the treated firms before and after matching, respectively. After the PSM, the probability density distributions of the two remaining groups are found to be remarkably consistent. These results demonstrate that our matching process eliminated the selectivity sample bias between the treated and control firms.

Table 5
Endogeneity: Heckman two-step method and PSM.

	(2)	(3)
	<i>TFP_acf</i>	<i>TFP_acf</i>
<i>DT</i>	0.0058*** (3.6714)	0.0085*** (4.1871)
<i>IMR</i>	0.1342*** (9.1825)	
Industry FE	Y	Y
Year FE	Y	Y
Firm cluster	Y	Y
CVs	Y	Y
R2	0.5285	0.5229
N	29,106	13,230

Note: Column (1)–(2) presents the results of the Heckman two-step method, and Column (3) presents the results of the PSM. The PSM ratio is 1:2. Parentheses report t-statistic; we employ ***, **, and * to represent the statistical significance level at 1%, 5%, and 10%, respectively. We controlled fixed effects in all columns at the year and industry-level. In every regression, this paper added all control variables, and clustered standard errors at the corporate level. For the definitions of all the variables, see Table A1.

Based on the matched enterprises, we re-estimate Eq. (8) and present the results in Column (2) of Table 5. We determined that $\hat{\beta}_1$ remains positive at the 1% significant level, suggesting that our benchmark conclusion is robust after overcoming the self-selection issue.

4.3.4. Placebo test

Following Hao et al. (2022), we use the placebo test method to assign the distribution of firm DT at random and re-estimate model (8) to reduce further the endogeneity concern regarding the unobserved factors. The aforementioned procedure is repeated 1000 times. Fig. 2 displays the probability density distribution and associated p-value for each estimated coefficient for the 1000 regressions. The estimated values of $\hat{\beta}_1$ are nearly identical (zero) and statistically insignificant. Therefore, our benchmark conclusion is not inferred from the factors that are not observed. The estimated values of $\hat{\beta}_1$ are nearly identical (zero), and most of the p-values are greater than 0.1 (i.e., statistically insignificant). Thus, our benchmark conclusion is not drawn from the unobserved factors.

4.4. Additional robustness analyses

In this section, this study conducts a series of additional robustness analyses to test the validity of our benchmark conclusion.

First, we calculate four alternative measures of firm DT: *DA*, *DigiTech*, *DB*, and *DR*. Specifically, *DA* represents the ratio of digital intangible assets to intangible assets; *DigiTech* denotes the word frequency of digital technology; and *DB* represents the word frequency of business model transformation. The natural logarithm of the word frequency is used. Companies with a low level of DT may be more sensitive to the marginal rise of DT and thus respond more quickly than those with a high level of corporate digitalization. In this case, productivity enhancement through DT may not be strictly linear. Therefore, the baseline regression model is unable to fully explain the effects of firm digitalization on productivity. Considering this outcome, and referring to Chen and Srinivasan (2019), we divide the value of firm DT into four quantiles and create a new variable, namely, *DR*, which takes the value of 1, 2, 3, or 4 if

the value of firm DT is in the first, second, third, or fourth quantiles. We replace the independent variable in Eq. (8) with the four alternative measures of firm DT and re-estimate Eq. (8). Table 6 summarizes the findings. We determine that $\hat{\beta}_1$ is positive at the 1% significant level, thereby confirming our benchmark conclusion.

Second, we compute two alternative measures of firm productivity, namely, the LP and OLS methods, which are denoted as *TFP_{lp}* and *TFP_{ols}*, respectively. Then, in Eq. (8), we substitute the two alternative measures of firm productivity for the dependent variable and re-estimate Eq. (8). Table 7 summarizes the results. We discover that $\hat{\beta}_1$ remains unchanged.

According to our review of firm productivity literature in Section 2, region-level factors also influence firm productivity (Demir et al., 2022; Kong et al., 2020). Therefore, we add the regional variables to Eq. (8) and re-estimate it. Table 8 shows the estimated results for the region-level controls, which are consistent with those in Section 4.3.1. Columns (1), (2), and (3) of Table 8 control the fixed effects at city level, the regional level, and both levels, respectively. We notice that $\hat{\beta}_1$ in all the columns of Table 8 remain unchanged, implying that our benchmark conclusion is robust after accounting for regional factors.

High-tech firms demonstrate higher R&D intensity (Bhattacharya et al., 2021) and extremely high productivity when compared to low-tech firms, which may bias our benchmark conclusion. Therefore, we exclude high-tech firms and re-estimate Eq. (8). The results are displayed in Column (1) of Table 9. We determine that $\hat{\beta}_1$ is 0.0049 and significant, indicating the robustness of our benchmark conclusion.

To examine the lag effect of firm digitalization on productivity, we replace the independent variable with its lag term, denoted as *L_DT*. The results are presented in Table 9. Column (2). We can see that $\hat{\beta}_1$ remains significantly positive, indicating that our benchmark conclusion is still robust after accounting for the lagged effect.

Finally, we include the firm fixed effects and industry-year fixed effects in the equation and re-estimate it Eq. (8). Table 10 summarizes the findings. The coefficient $\hat{\beta}_1$ supports our benchmark conclusion.

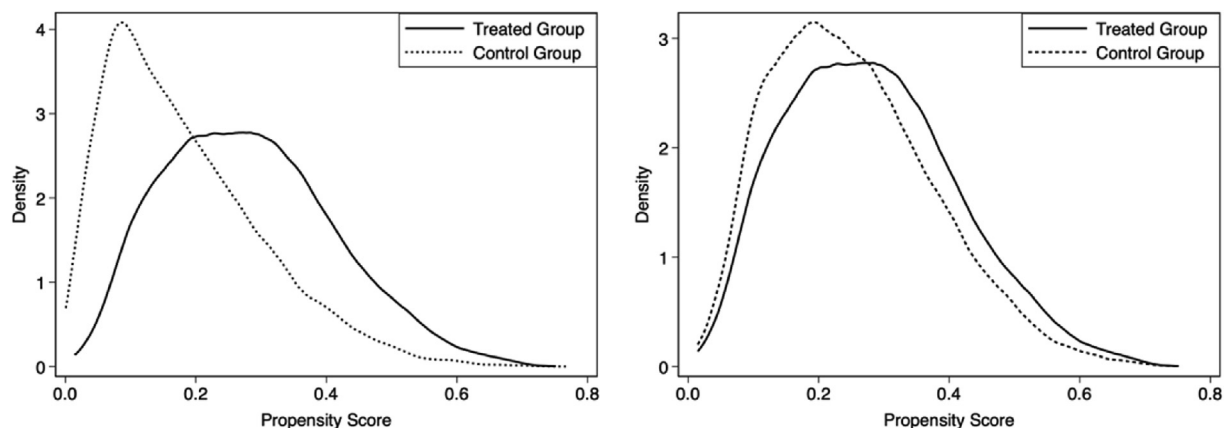


Fig. 1. Nuclear density distribution comparison (before and after matching).

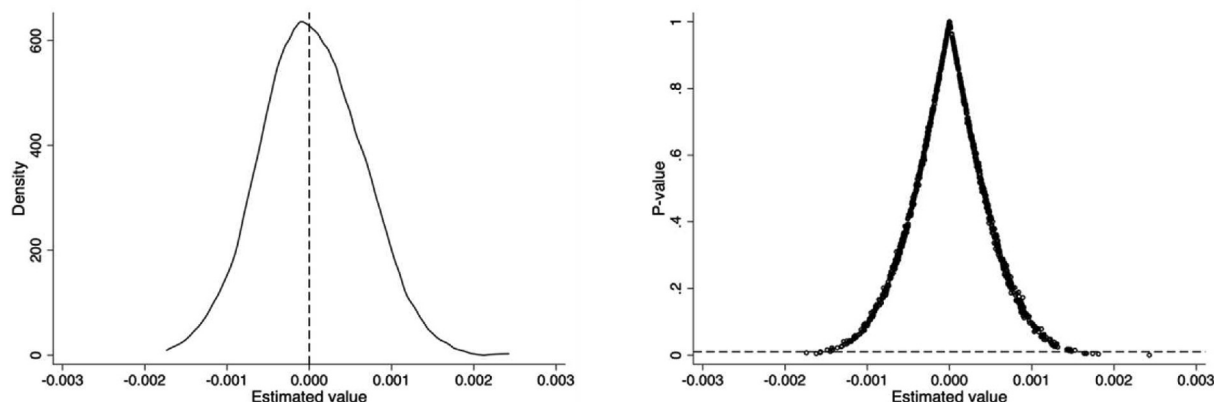


Fig. 2. Probability density distribution and p-value of estimated coefficients.

Table 6
Robustness tests: alternative measures of digital transformation.

	(1)	(2)	(3)	(4)
	<i>TFP_acf</i>	<i>TFP_acf</i>	<i>TFP_acf</i>	<i>TFP_acf</i>
<i>DA</i>	1.1474** (2.0213)			
<i>DigiTech</i>		0.0110*** (6.7297)		
<i>DB</i>			0.0039** (2.3877)	
<i>DR</i>				0.0055*** (3.3222)
Industry FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Firm cluster	Y	Y	Y	Y
CVs	Y	Y	Y	Y
R2	0.5160	0.5250	0.5231	0.5233
N	17,831	29,181	29,181	29,181

Note: parentheses report t-statistic; we employ ***, **, and * to represent the statistical significance level at 1%, 5%, and 10%, respectively. We controlled fixed effects in all columns at the year and industry-level. In every regression, this paper added all control variables, and clustered standard errors at the corporate level. For the definitions of all the variables, see Table A1.

Table 7
Robustness checks: alternative productivity measures.

	(1)	(2)
	<i>TFP_lp</i>	<i>TFP_ols</i>
<i>DT</i>	0.0424*** (7.4264)	0.0317*** (5.8280)
Industry FE	Y	Y
Year FE	Y	Y
Firm cluster	Y	Y
CVs	Y	Y
R2	0.7809	0.8495
N	29,181	29,181

Note: parentheses report t-statistic; we employ ***, **, and * to represent the statistical significance level at 1%, 5%, and 10%, respectively. We controlled fixed effects in all columns at the year and industry-level. In every regression, this paper added all control variables, and clustered standard errors at the corporate level. For the definitions of all the variables, see Table A1.

Table 8
Robustness checks: controlling regional factors.

	(1)	(2)	(3)
	<i>TFP_acf</i>	<i>TFP_acf</i>	<i>TFP_acf</i>
<i>DT</i>	0.0069*** (3.8106)	0.0058*** (3.5948)	0.0060*** (3.2786)
<i>EL</i>	−0.0004 (−1.0819)		0.0003 (1.0960)
<i>GL</i>	0.0254 (0.7411)		0.0423 (1.0927)
<i>OL</i>	2.6971*** (3.6674)		1.6056* (1.9584)
Industry FE	Y	Y	Y
Year FE	Y	Y	Y
City FE	N	Y	Y
Firm cluster	Y	Y	Y
CVs	Y	Y	Y
R2	0.5400	0.5487	0.5653
N	20,091	29,168	20,089

Note: parentheses report t-statistic; we employ ***, **, and * to represent the statistical significance level at 1%, 5%, and 10%, respectively. In Column (1), we have controlled fixed effects at the year and industry level. In Columns (2) and (3), we have controlled fixed effects at the city, year, and industry level. In every regression, this paper added all control variables, and clustered standard errors at the corporate level. For the definitions of all the variables, see Table A1.

5. Heterogeneity analysis

The main effect may demonstrate heterogeneity in firm industry characteristics. In the literature, heterogeneous productivity in upstream and downstream industries has been extensively analyzed (e.g., Bas & Causa, 2013; Cetté et al., 2017). First, on China's production market, SOEs typically dominate upstream industries, whereas private companies and other SOEs compete in downstream industries. Consequently, market competition in the downstream industries is relatively greater than that in the upstream industries. Moreover, enterprises in the downstream industries may receive a greater incentive to improve their technological innovation to maintain a competitive advantage. Furthermore, privately owned firms

Table 9
Robustness tests additional robustness testing.

	(1)	(2)
	<i>TFP_acf</i>	<i>TFP_acf</i>
<i>DT</i>	0.0049** (2.2936)	
<i>L-DT</i>		0.0066*** (3.9968)
Industry FE	Y	Y
Year FE	Y	Y
Firm cluster	Y	Y
CVs	Y	Y
R2	0.8110	0.5193
N	29,054	24,969

Note: Column (1) presents the results when the sample of high-tech companies is excluded, and Column (2) presents the results when the independent variable is replaced with its lagged term. Parentheses report t-statistic; we employ ***, **, and * to represent the statistical significance level at 1%, 5%, and 10%, respectively. We controlled fixed effects in all columns at the year and industry-level. In every regression, this paper added all control variables, and clustered standard errors at the corporate level. For the definitions of all the variables, see Table A1.

Table 10
Robustness checks: alternative fixed effects.

	(1)	(2)
	<i>TFP_acf</i>	<i>TFP_acf</i>
<i>DT</i>	0.0059*** (3.6325)	0.0075*** (5.0468)
Year FE	N	Y
Industry-year FE	Y	N
Firm FE	N	Y
Firm cluster	Y	Y
CVs	Y	Y
R2	0.5129	0.8015
N	16,393	29,055

Note: parentheses report t-statistic; we employ ***, **, and * to represent the statistical significance level at 1%, 5%, and 10%, respectively. In Column (1), we have controlled the joint fixed effects of industry and year. In every regression, this paper added all control variables, and clustered standard errors at the corporate level. In Column (2), we have controlled fixed effects at the year and corporate level. For the definitions of all the variables, see Table A1.

were found to dominate technological upgrading in China (Walheer & He, 2020), whereas SOEs perform poorly in innovation due to their political attribution. In addition, downstream industries, particularly consumer industries, exhibit high demand elasticity (Jiang, Chen, et al., 2022). Downstream industries may be subject to changes in consumers adapting to changing consumer behaviors in the digital age and may motivate businesses to implement DT (Jiang, Du, & Chen, 2022; Verhoef et al., 2021). The imperativeness of DT increases for enterprises in downstream industries. Considering these facts, we conjecture that the DT of downstream industry enterprises demonstrates a greater impact on their productivity via the technological innovation channel than that of upstream industry enterprises.

Using the National Bureau of Statistics and Li et al.'s (2015) classification standard, we categorize industries according to

their position in the industry chain as upstream and downstream.¹ We build a new dummy variable, namely, *Upstream* equaling 1 if the firm belongs to the upstream industries sample, and 0 otherwise. Next, we divide the entire sample into two subsamples based on the value of *Upstream* and re-estimate Eq. (8). The results are shown in Table 11. We find that the coefficient of *DT* is significantly positive only in the sample of downstream industries, but not in the sample of upstream industries. Moreover, we add the interactive term of *DT* and *Upstream* to Eq. (8) and rerun the regression. The outcomes are shown in Column 3 of Table 11. The coefficient of *Upstream* × *DT* is negative and statistically significant at the 1% level, indicating that *DT* positively impacts downstream industries, confirming our previous conclusion. In summary, these findings support our hypothesis that the positive impact of *DT* on productivity in downstream industries is significant.

6. Potential mechanism analysis

This section discusses the potential mechanisms of the positive link between *DT* and productivity. As discussed in Section 2.2, the potential channels crucial for enhancing firm productivity are technological innovation, human capital, operating capacity, and investment efficiency. By evaluating the improvement effect of *DT* on the mediating variables, we investigate these potential channels.

Table 11
Heterogeneity analysis: firm industry attributes.

	(1)	(2)	(3)
	<i>Upstream</i> = 1	<i>Upstream</i> = 0	
	<i>TFP_acf</i>	<i>TFP_acf</i>	<i>TFP_acf</i>
<i>DT</i>	−0.004 (−0.7026)	0.008*** (4.7217)	0.0083*** (5.1093)
<i>Upstream</i> × <i>DT</i>			−0.0219*** (−3.8714)
Industry FE	Y	Y	Y
Year FE	Y	Y	Y
Firm cluster	Y	Y	Y
CVs	Y	Y	Y
R2	0.569	0.521	0.5247
N	3187	25,994	29,181

Note: parentheses report t-statistic; we employ ***, **, and * to represent the statistical significance level at 1%, 5%, and 10%, respectively. We controlled fixed effects in all columns at the year and industry-level. In every regression, this paper added all control variables, and clustered standard errors at the corporate level. For the definitions of all the variables, see Table A1.

¹ According to the National Bureau of Statistics and Li et al. (2015), the upstream industries include mining; raw material manufacturing (including petroleum processing and steel smelting); electricity, gas, and water production and supply; transportation; warehousing and postal; telecommunications; and banking. Meanwhile, the downstream industries include construction; agriculture, forestry, animal husbandry, and fishery; general processing and manufacturing (including food, beverage, textile, clothing, furniture, paper printing, rubber, and other industries); wholesale and retail; accommodations and catering; and real estate.

6.1. Technological innovation channel

The technological innovation channel indicates that firm DT may improve innovation, thereby increasing productivity. We construct two new proxy variables for firm innovation, namely, *Innovation1* and *Innovation2*. *Innovation1* denotes the proportion of R&D investment expenditure in operating income. R&D investment expenditure can be thought of as R&D-related fixed assets, including R&D personnel salaries and wages; it is closely related to an enterprise's level of technological innovation (Xie et al., 2022). Meanwhile, *Innovation2* refers to the natural log of the number of authorized invention patents. Invention patents are thought to involve significant technological advancements and can thus be used to assess a company's technological innovation (Kong et al., 2020; Wu et al., 2020). Table A3 displays the descriptive statistics for *Innovation1* and *Innovation2*. Next, we discover that the mean proportion of R&D investment expenditure in the operating income is 4.66%, and the mean natural log of the number of authorized invention patents is 1.43, indicating that Chinese firms' innovation capability is relatively low. Then, in Eq. (8), we replace the dependent variable with *Innovation1* and *Innovation2* and re-estimate Eq. (8). Table 12 summarizes the results. Regardless of which firm innovation proxy variable we use, the coefficient of innovation remains positive and significant at the 1% level. Hence, we can conclude that firm DT increases productivity by enhancing firm innovation.

6.2. Human capital channel

The human capital channel indicates that a company's DT may increase productivity by leveraging its human resources. A firm's human capital refers to its personnel's productive capacities (Backman, 2014; Becker, 1962) and can be measured as the proportion of its qualified labor force (Backman, 2014; He et al., 2022). Therefore, following Backman (2014), we construct two new proxy variables for a firm's human capital based on the dimension of education and skills: *Capital1* and *Capital2*. *Capital1* denotes the proportion of employees with a bachelor's

degree or higher from the education dimension. According to the nature of the work, a company's workforce can be categorized as technical, production, sales, financial, and so on. Among these various types of personnel, the scale of technical personnel can represent the skills dimension of the company's human capital (Sun et al., 2020). Therefore, we employ *Capital2*, the proportion of technical personnel, to measure a company's human capital. The descriptive statistics for *Capital1* and *Capital2* are shown in Table A3. The average percentage of employees with a bachelor's degree or higher is 31.66%, and the average percentage of technical personnel is 21.66%, indicating that Chinese companies are dominated by low-skilled labor, which is consistent with China's relatively low human capital. Then, we substitute *Capital1* and *Capital2* for the dependent variable in Eq. (8) and re-estimate Eq. (8). The outcomes are shown in Table 13. Human capital coefficient remains positive and statistically significant at the 1% level regardless of the proxy variable used to measure a company's human capital. Therefore, we can conclude that the DT of a firm increases its productivity by improving its human capital.

6.3. Operating capacity channel

According to the operating capacity channel, a company's DT may promote its productivity by boosting operating capacity at the firm-level. Operating capacity is a traditional accounting metric that describes a company's ability to allocate resources (Xiao et al., 2021). Therefore, we choose two operating capacity indicators: *Capacity1* and *Capacity2*. *Capacity1* denotes the total asset turnover, whereas *Capacity2* denotes fixed asset turnover. Table A3 summarizes the descriptive statistics. The mean value of the percentage of sales in total assets (*Capacity1*) is 0.624, whereas that in fixed assets (*Capacity2*) is 8.796, which are in line with existing literature (Jiang, Chen, et al., 2022). Then, we re-estimate Eq. (8) by substituting *Capacity1* and *Capacity2* for the dependent variable. Table 14 displays the estimated results. The coefficient of operating capacity remains positive and significant at the 1% level regardless of the proxy variable we use for firm operating

Table 12
Potential mechanism analysis: technological innovation channel.

	(1) <i>Innovation1</i>	(2) <i>Innovation2</i>
DT	0.091*** (6.8989)	0.343*** (7.4616)
Industry FE	Y	Y
Year FE	Y	Y
Firm cluster	Y	Y
CVs	Y	Y
R2	0.375	0.413
N	14,138	20,169

Note: Parentheses report t-statistic; We employ ***, **, and * to represent the statistical significance level at 1%, 5%, and 10%, respectively. We controlled fixed effects in all columns at the year and industry-level. In every regression, this paper added all control variables, and clustered standard errors at the corporate level. For the definitions of all the variables, see Table A1.

Table 13
Potential mechanism analysis: human capital channel.

	(1) <i>Capital1</i>	(2) <i>Capital2</i>
DT	1.965*** (8.4590)	1.692*** (9.9076)
Industry FE	Y	Y
Year FE	Y	Y
Firm cluster	Y	Y
CVs	Y	Y
R2	0.455	0.466
N	16,905	23,676

Note: parentheses report t-statistic; we employ ***, **, and * to represent the statistical significance level at 1%, 5%, and 10%, respectively. We controlled fixed effects in all columns at the year and industry-level. In every regression, this paper added all control variables, and clustered standard errors at the corporate level. For the definitions of all the variables, see Table A1.

Table 14
Potential mechanism analysis: operating capacity channel.

	(1)	(2)
	<i>Capacity1</i>	<i>Capacity2</i>
<i>DT</i>	0.016*** (4.3180)	0.578*** (2.8018)
Industry FE	Y	Y
Year FE	Y	Y
Firm cluster	Y	Y
CVs	Y	Y
R2	0.382	0.227
N	29,181	29,180

Note: parentheses report t-statistic; we employ ***, **, and * to represent the statistical significance level at 1%, 5%, and 10%, respectively. We controlled fixed effects in all columns at the year and industry-level. In every regression, this paper added all control variables, and clustered standard errors at the corporate level. For the definitions of all the variables, see Table A1.

capacity. Therefore, the results in Table 14 thus support our hypothesis that increasing operating capacity through firm DT increases productivity.

6.4. Investment efficiency channel

The investment efficiency channel denotes how a firm's DT can boost productivity by improving firm-level investment efficiency. According to previous research (Biddle et al., 2009; Chen, Hope, et al., 2011), investment efficiency is associated with enterprise deviation from the optimal level of investment. By measuring the residuals of investment expenditure to investment opportunities (represented by growth in sales), we calculate the value of investment efficiency following Biddle et al. (2009). The following is a description of the regression model:

$$Inv_{i,t} = \beta_0 + \beta_1 Growth_{i,t-1} + \varepsilon_{i,t} \quad (12)$$

where $Inv_{i,t}$ refers to the investment expenditure of firm i in year t , and is calculated by a firm's net cash payments for long-term assets scaled by the lagged total assets (Chen, Sun, et al., 2011; Hu et al., 2019); $Growth_{i,t-1}$ refers to the percentage change in firm i 's operating revenue in year $t-1$. For each industry-year, we estimate Eq. (12) and exclude industries with fewer than 20 observations in a given year. The CSMAR database is used to obtain relevant data. Then, we take the absolute value of the residual estimated by Eq. (12) and denote it as $InvEff_Biddle$.

The relationship between investment and income growth may differ when income increases or decreases; thus, we follow Chen, Hope, et al. (2011) and create a piecewise linear regression equation:

$$Inv_{i,t} = \beta_0 + \beta_1 NEG_{i,t-1} + \beta_2 Growth_{i,t-1} + \beta_3 NEG \times Growth_{i,t-1} + \varepsilon_{i,t} \quad (13)$$

where $NEG_{i,t-1}$ is a dummy variable that takes the value of one if firm i 's operating revenue growth in year $t-1$ is negative,

and zero otherwise. All the other variables are consistent with those in Eq. (12). Next, we take the absolute value of the residual estimated by Eq. (13) and denote it as $InvEff_Chen$. The descriptive statistics of $InvEff_Biddle$ and $InvEff_Chen$ are summarized in Table A3. Both $InvEff_Biddle$ and $InvEff_Chen$ exhibit 26,767 observations and a mean value of 0.04, implying that Chinese listed companies suffer from investment inefficiency, on average, but the value is relatively low.

Next, we replace the dependent variable of Eq. (8) with $InvEff_Biddle$ and $InvEff_Chen$ and re-estimate Eq. (8). Table 15 displays the estimated results. Regardless of the proxy variable used to measure firm investment efficiency, the coefficient remains positive and statistically significant. Accordingly, the findings in Table 15 suggest that firm DT boosts productivity by increasing investment efficiency.

7. Further analysis

This section further discusses the advantages of increasing business productivity from the standpoint of firm DT. Our review of the literature on firm productivity reveals that firms choose their production strategies to increase their profits (Levinsohn & Petrin, 2003; Mo et al., 2021). As a result, increased profitability may result from improved firm productivity. Following Saygili et al. (2022), in this section, to determine whether DT increases profitability by increasing productivity, we focus on return on assets (denoted as ROA) and gross margin (denoted as $Margin$), which represent for firm profitability. In line with Kim et al. (2021), we estimate a two-stage model to determine the effect of the increased firm productivity brought on by DT on profitability. In the first stage, we obtain the fitted value of TFP_acf (denoted as $\widehat{TFP_acf}$) from Eq. (8). In the second stage, we regress the fitted value of TFP_acf ($\widehat{TFP_acf}$) on business profitability, with all the other settings consistent with those in Eq. (8).

$$ROA_{i,t} \text{ or } Margin_{i,t} = \beta_0 + \beta_1 \widehat{TFP_acf}_{i,t} + \gamma CVs_{i,t} + \lambda_t + \eta_j + \varepsilon_{i,t} \quad (14)$$

Table 15
Potential mechanism analysis: investment efficiency channel.

	(1)	(2)
	<i>InvEff_Biddle</i>	<i>InvEff_Chen</i>
<i>DT</i>	-0.001** (-2.3883)	-0.001* (-1.8840)
Industry FE	Y	Y
Year FE	Y	Y
Firm cluster	Y	Y
CVs	Y	Y
R2	0.082	0.081
N	26,265	26,265

Note: parentheses report t-statistic; we employ ***, **, and * to represent the statistical significance level at 1%, 5%, and 10%, respectively. We controlled fixed effects in all columns at the year and industry-level. In every regression, this paper added all control variables, and clustered standard errors at the corporate level. For the definitions of all the variables, see Table A1.

Table 16
Further analysis.

	(1)	(2)
	<i>ROA</i>	<i>Margin</i>
TFP_acf	1.6312*** (9.1126)	0.1110*** (3.3973)
Industry FE	Y	Y
Year FE	Y	Y
Firm cluster	Y	Y
CVs	Y	Y
R2	0.5925	0.8264
N	29,181	29,181

Note: parentheses report t-statistic; we employ ***, **, and * to represent the statistical significance level at 1%, 5%, and 10%, respectively. We controlled fixed effects in all columns at the year and industry-level. In every regression, this paper added all control variables, and clustered standard errors at the corporate level. For the definitions of all the variables, see Table A1.

The pertinent results are shown in Table 16. We can see that the coefficients of TFP_acf in Columns (1) and (2) are statistically significant and positive, indicating that firm productivity can significantly increase profitability. In conjunction with the benchmark conclusion, we believe that DT can increase profitability by boosting firm productivity.

8. Conclusion

This study mainly examines the effects of firm digitalization on productivity in the context of the digital era. We create a Chinese dictionary containing DT keywords using a deep learning model and obtain a comprehensive predictor for firms' DT. Using data from Chinese listed companies from 2007 to 2020, we discover that firms' DT demonstrates a significant and positive impact on their productivity. In addition, to address potential endogeneity issues, we use the instrumental 2SLS, Heckman, PSM, and placebo test methods. After we conduct a series of robustness analyses, the baseline empirical results remain valid, including using alternative measures of a firm's DT and productivity, controlling for city level factors in the regression, excluding high-tech companies, lagging the independent variable, and employing firm fixed effects and industry-year fixed effects. Then, we verify whether heterogeneity exists in firm industry attributes and discover that the improvement effect is stronger in firms in downstream industries. In terms of mechanism channels, our findings suggest that improving Chinese firms' productivity can be accomplished by promoting technological innovation, human capital, operating capability, and investment efficiency through DT. Further investigation reveals that the enhancement of firm productivity brought about by DT can result in increased profitability.

Our study's findings and conclusions demonstrate significant implications for relevant government departments and firm decision-making in China and other countries. First, our research confirms that firm DT leads to increased productivity. Therefore, managers should consult our findings to develop firm DT and improve their firm's technological innovation, human capital, operating capability, and investment efficiency,

resulting in firm productivity gains. Second, our research shows that DT demonstrates a significant impact on the Chinese economy; therefore, relevant government agencies should adhere to the development of digital technologies and the digital economy. Third, special attention should be paid to the development of a digital workforce to adapt to firms' DTs and the digital era's development. Finally, heterogeneous analysis reveals that the productivity-enhancing effect is more pronounced in firms in downstream industries. Thus, the government must also consider company heterogeneity, providing greater DT support to firms in downstream industries.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A.

Table A1
Definition of variables

Variable	Definition
$y_{i,t}$	The natural log of value-added
$l_{i,t}$	The natural log of labor input
$k_{i,t}$	The natural log of capital input
$\omega_{i,t}$	$\omega_{i,t} = \alpha_0 + \nu_{i,t}$
TFP_acf	Firm's productivity calculated by ACF method
DT	The overall degree of firm-level digital transformation
$asset$	The natural log of total asset
age	The natural log of established age
$leverage$	The proportion of total liabilities in all assets
roe	Return on equity
tax	Firm's tax rate
$growth$	Operating income growth compared to the previous year
$director$	The natural log of the number of directors
$opinion$	A dummy variable equaling to one if firm's audit opinion is standard and qualified and zero otherwise
$duality$	A dummy variable equaling to one if there is a combination of CEO and chairman of the board and otherwise 0
$outdirrate$	The proportion of outside directors on the board
$state$	A dummy variable equaling to 1 if a company is state-owned and otherwise 0
$Upstream$	A dummy value that equals to one if firm belongs to upstream industries and zero otherwise
IV	Instrument variable, represent as the average value of digital transformation of other enterprises in the same industry
SD_TFP	Standard deviation of firms' productivity in the industry
HHI	The industry-level Herfindahl–Hirschman Index of the in which firm operates.
$BroadBand$	A dummy variable taking 1 if city suffers from Broadband China policy shock and zero otherwise
EL	City's GDP growth rate
GL	City's expenditure within the general budget of local government divided by GDP

(continued on next page)

Table A1 (continued)

Variable	Definition
<i>OL</i>	City's actual use of foreign capital divided by GDP
<i>Heckman_dummy</i>	A dummy variable takes the value of one if firm's digital transformation is higher than the average and zero otherwise.
<i>IMR</i>	The Inverse Mill's Ratio
<i>PSM_dummy</i>	A dummy variable takes the value of one if firm's average level of digital transformation in all sample years is higher than 80% quantile and zero otherwise.
<i>DA</i>	The ratio of digital intangible assets to all intangible assets
<i>DigiTech</i>	The word frequency of digital technology
<i>DB</i>	The word frequency of business model transformation
<i>DR</i>	Four quantiles of the value of firm digital transformation
<i>TFP_lp</i>	Firm's productivity calculated by LP method
<i>TFP_ols</i>	Firm's productivity calculated by OLS method
<i>L_DT</i>	Lag term of <i>Digitaltrans</i>
<i>Innovation1</i>	The proportion of R&D investment expenditure to operating income
<i>Innovation2</i>	The natural log of the number of authorized invention patents
<i>Capital1</i>	The proportion of employees with a bachelor's degree or above from education dimension
<i>Capital2</i>	The proportion of technical personnel to firm's employees from skills dimension
<i>Capacity1</i>	Turnover of total asset
<i>Capacity2</i>	Turnover of fixed asset
<i>Innovation1</i>	Firm's investment efficiency calculated by Biddle method
<i>Innovation2</i>	Firm's investment efficiency calculated by Chen method
$\widehat{TFP}_{acf}$	The fitted value of TFP_{acf} from Eq. (8)
<i>ROA</i>	Return on assets
<i>Margin</i>	Gross margin

Table A2

Balance test for PSM

Variable	Matched	Treated	Control	Bias	T-statistics	p-value
<i>asset</i>	U	21.6620	22.2380	−48.50%	−31.76	0.000
	M	21.6620	21.6600	0.20%	0.12	0.904
<i>age</i>	U	2.6159	2.7739	−40.10%	−28.33	0.000
	M	2.6159	2.6160	0%	−0.02	0.981
<i>leverage</i>	U	0.3644	0.4555	−46.40%	−31.37	0.000
	M	0.3644	0.3690	−2.40%	−1.36	0.173
<i>roe</i>	U	0.0611	0.0511	6.90%	4.61	0.000
	M	0.0611	0.0610	0%	0.02	0.987
<i>tax</i>	U	0.0257	0.0369	−32.30%	−19.24	0.000
	M	0.0257	0.0250	2%	1.57	0.116
<i>growth</i>	U	0.4677	0.4144	4.90%	3.08	0.002
	M	0.4677	0.4721	−0.40%	−0.20	0.844
<i>director</i>	U	2.0962	2.1504	−27.40%	−18.86	0.000
	M	2.0962	2.0981	−1%	−0.53	0.599
<i>opinion</i>	U	0.9812	0.9667	9.10%	5.84	0.000
	M	0.9812	0.9813	−0.10%	−0.03	0.973
<i>duality</i>	U	0.3754	0.2209	34.30%	24.87	0.000
	M	0.3754	0.3719	0.80%	0.41	0.685
<i>outdirrate</i>	U	0.3796	0.3723	13.50%	9.45	0.000
	M	0.3796	0.3794	0.40%	0.2	0.84
<i>state</i>	U	0.2340	0.4457	−45.90%	−30.32	0.000
	M	0.2340	0.2337	0.10%	0.03	0.974

Table A3

Descriptive statistics for mediating variables

Variable	N	Mean	S.D.	Min	P25	P50	P75	Max
<i>Innovation1</i>	20,437	4.660	4.543	0.030	1.920	3.620	5.530	26.100
<i>Innovation2</i>	14,449	1.430	1.235	0.000	0.693	1.099	2.197	5.342
<i>Capital1</i>	17,139	31.660	21.180	3.790	14.950	25.930	43.620	88.740
<i>Capital2</i>	23,974	21.160	17.480	1.430	9.760	15.540	26.44	82.980
<i>Capacity1</i>	29,837	0.624	0.421	0.081	0.345	0.527	0.774	2.328
<i>Capacity2</i>	29,834	8.796	21.960	0.289	1.624	3.050	6.319	169.200
<i>Innovation1</i>	26,767	0.042	0.042	0.001	0.015	0.032	0.051	0.243
<i>Innovation2</i>	26,767	0.041	0.042	0.001	0.015	0.031	0.051	0.240

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