


# Digitalization of the Business Environment and Innovation Efficiency of Chinese ICT Firms

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## ABSTRACT

This study investigates how the digital business environment affects firms' innovation input variables. It was discovered that digitization leads to ongoing corporate environment optimization, which improves the effectiveness of innovation. One of the institutional environment factors, digitalization, increases the redundancy of government subsidies on businesses' investments in innovation. It also helps to eliminate duplication in innovation investment through the financial environment and the protection of legal rights. With increasing marketization in the informal institutional framework, the degree of R&D investment redundancy lowers while R&D human resource investment redundancy grows. Digitization not only lowers the grade of innovation, but it also has a negative association with the duplicate nature of commercial R&D investments. The authors' research combines institutional environment theory and digital development to establish a new empirical foundation for corporate development in order to boost innovation efficiency.

## KEYWORDS

Business Environment, Innovation Efficiency, Input Factors, Input Redundancy, The Three-Stage DEA Model

## 1. INTRODUCTION

The institutional theory posits that an effective system can foster economic growth and development, with the business environment serving as a tangible manifestation of this system (Struckell et al., 2022; R. Wang et al., 2021). The business environment encompasses the policies, regulations, and socio-economic factors within a country or region that directly impact enterprise operations, such as

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government policies, legal regulations, market competition, social culture, and infrastructure (Chang & Chen, 2021; Do et al., 2022). According to institutional theory, a robust legal system is crucial for safeguarding property rights and contractual agreements (Brousseau et al., 2011; Y. Yang et al., 2021). Additionally, a sound system should support market competition while preventing monopolies and undue intervention, thereby stimulating innovation and competitiveness among enterprises (Jiang et al., 2023; Pasinetti, 2021; Wang et al., 2022). Ultimately, a strong system can promote entrepreneurship and innovation, augment market efficiency, and improve overall business competitiveness.

The business environment has been profoundly affected by the advent of digital transformation (Mann et al., 2022; Y. Zhang et al., 2023; Liu et al., 2022). Firstly, it enables enhanced information exchange and collaboration, which expands the market size while reducing barriers to entry and streamlining innovation and entrepreneurship (Rosado-Cubero et al., 2023; L. Yu et al., 2023). Secondly, digital technologies can automate numerous internal processes, which in turn reduces cycle times, cuts costs, improves production efficiency and enhances product quality (H. Zhang et al., 2023). Finally, digital transformation has resulted in the emergence of new business models and opportunities, offering companies novel avenues for growth and development (Ancillai et al., 2023; Marcon et al., 2022). In the current digital era, enterprise competitiveness is increasingly predicated on intangible assets such as technology, data, and knowledge, thus transforming the traditional business environment (Şimşek et al., 2022). Consequently, digital transformation renders a multifaceted impact on the business environment, encompassing both beneficial effects and disruptions that challenge conventional business environment models (Wani et al., 2021; Liu et al., 2022).

The impact of the business environment on enterprise innovation can be seen in numerous ways (Ghosh et al., 2021; Kraus et al., 2022). Firstly, a positive business environment provides enterprises with sufficient innovation resources, which directly influences the effectiveness of their innovation implementation (Li et al., 2023, 2023). Secondly, a favorable business environment adequately protects the intellectual property (IP) rights of enterprises and supports their technological research and development (Zhao et al., 2022; Ding et al., 2022). This protection enables enterprises to engage more actively in technological innovation (Z. Chen, 2022; Scherrer & Perrig, 2021). Thirdly, government policies and services can promote innovation investment and practices by facilitating innovative activities among enterprises (Böttcher et al., 2022; Y. Jia et al., 2023; Ozen & Ozturk-Kose, 2023). Fourth, regions or countries with a robust business environment have broader and more diversified market demand, providing enterprises with greater opportunities to innovate in products and technologies (K. H. Choi & Kwon, 2023; Karami et al., 2022). Fifthly, a competitive business environment incentivizes enterprises to constantly improve their innovation strength and competitiveness, thereby promoting technological progress and upgrading the entire industry (Amouri et al., 2021; Hoskins & Carson, 2022; Wang et al., 2023). Thus, the business environment has a significant impact on the innovation activities and outcomes of enterprises. A positive business environment can provide enterprises with improved conditions for innovation and development, fostering greater competitive advantages in the marketplace.

Corporate innovation is currently a topic of great interest to researchers, who have contributed many findings from multiple perspectives on wind farms. However, despite this progress, there are still some gaps in the existing research. Firstly, scholars have primarily used methods such as empirical regression and case studies in their research, focusing on individual firms and innovation elements. As a result, they have been unable to explain the underlying logic behind corporate innovation comprehensively. Secondly, most studies have concentrated on internal factors such as employee quality, technology base, and ownership nature, as well as external policy factors like R&D subsidies, tax incentives, and policy support, without taking into account a comprehensive, multi-level, and multi-faceted research perspective. Lastly, current research on corporate innovation has inadequate theoretical construction, with many studies describing phenomena without strong theoretical support.

Our research offers several improvements to the existing literature in order to address gaps that currently exist. Firstly, we utilized a three-stage DEA method to measure the innovation efficiency

of listed ICT firms. By measuring the impact of various environmental variables on the redundancy of firms' innovation inputs, we were able to generate results that more accurately reflect the real situation. Additionally, we employed the Malmquist index model to analyze the dynamic trend of innovation efficiency changes among ICT firms over a ten-year period and assess the impact of different factors on innovation efficiency. Furthermore, we utilized the Tobit model to quantify the factors with the greatest impact on the innovation efficiency of listed ICT companies. This approach provides a comprehensive understanding of ICT conglomerates as a whole, as well as the underlying mechanisms that affect innovation efficiency. Secondly, unlike previous studies that have mainly focused on examining the internal and external environment of individual firms, our study explores the impact of the digital business environment on the innovation efficiency of ICT firms from multiple perspectives. We also construct a comprehensive analytical framework for this purpose. Lastly, while prior research has primarily relied on firm endowment theories, such as competitive advantage theory and factor endowment theory, to explain innovation; our study takes a different approach by adopting institutional theory to examine the impact of the business environment on firms' innovation efficiency. This provides a theoretical basis for promoting innovation efficiency from a broader societal perspective.

## 2. LITERATURE REVIEW AND HYPOTHESES DEVELOPMENT

The digital transformation has brought about several positive impacts on the business environment, including the following: Firstly, the digital business environment simplifies interactions between businesses and government, reducing time and labor costs (Teece, 2018; Wiredu et al., 2021; M. Yang & Han, 2021). Secondly, it enhances fairness and transparency in market competition through open and transparent information and data-sharing mechanisms (Dong et al., 2023; Shin & Park, 2019). Finally, it provides enterprises with comprehensive and accurate information on market intelligence, technological developments, and talent resources, fostering innovation and development (Delorme, 2023; Mota et al., 2023). Therefore, optimizing the business environment through digital transformation and establishing a robust institutional framework are effective means of promoting enterprise innovation.

The impact of a digital business environment on a company's innovation resources is comprehensive. It can facilitate the provision, transformation, and application of these resources. Firstly, the digital business environment offers enterprises more information and data resources, enabling them to better comprehend market and industry conditions, thus determining their innovation direction and strategy more effectively (Varadarajan, 2020; Zafari et al., 2023; Wang et al., 2022). Secondly, it enhances the innovation capability of enterprises. Digital technology enables companies to develop and innovate rapidly and efficiently, reducing costs and risks involved in the process (H. Chen & Tian, 2022; Mithani, 2023). Finally, digital platforms facilitate better transformation and application of companies' innovation resources. Companies can manage their intellectual property rights more efficiently, and access more financing channels and collaboration opportunities, thus better converting innovation resources into business value (Marcon et al., 2022; Varadarajan, 2020; F. Yu et al., 2023). In summary, the digital business environment plays a crucial role in promoting the discovery and application of innovation resources, empowering enterprises to seize opportunities, enhance their market competitiveness, and increase their profitability.

The digital business environment has a positive impact on the protection of companies' legitimate rights and interests, in addition to its profound impact on innovation resources (Dahabiyeh & Constantinides, 2022; Laifi & Jossierand, 2016). Firstly, it provides more transparency and information, enabling companies to better grasp market dynamics and protect their legitimate rights and interests in a timely manner (D. Y. Choi & Perez, 2007; Zhang et al., 2023). Secondly, digital platforms offer a more transparent and secure market environment for businesses, increasing trust and promoting collaboration that protects their legitimate rights and interests in business dealings (Delorme, 2023;

Dong et al., 2023; Karami et al., 2022). Thirdly, it enhances compliance awareness and management capabilities of enterprises, allowing them to comply with relevant laws and regulations more easily, manage risks and disputes in a timely manner, and conduct refined and scientific risk management and internal management (Ghosh et al., 2021; Ozen & Ozturk-Kose, 2023). Finally, the digital business environment helps improve the level of intellectual property rights protection. Digital platforms effectively prevent IPR infringement, misappropriation, and theft, protecting innovation achievements and IPR interests of enterprises, while also providing convenient and efficient means of IP protection (Böttcher et al., 2022; Karami et al., 2022). Therefore, the digital business environment positively impacts enterprises' legitimate rights and interests, enhancing their competitiveness and long-term development capabilities.

A digital business environment can optimize innovative policy measures and improve the efficiency of policy implementation (Boateng et al., 2021; Delorme, 2023; Rosado-Cubero et al., 2023). By establishing a digital information sharing platform, policy makers, regulators, and businesses can quickly share information and data, reducing wasted resources and uncertainty in policy implementation (Delorme, 2023; F. Yu et al., 2023). Digital technology allows for the rapid replication of successful innovation experiences and standardizes the implementation process of relevant innovation policies, thereby enhancing the efficiency and quality of policy implementation (Li et al., 2023; Marcon et al., 2022; Liu et al., 2023). This optimizes the flow of innovation capital, reduces financing costs, and increases the dynamism of corporate innovation through innovative financial instruments and investment mechanisms (Amouri et al., 2021; Y. Zhang et al., 2023). Additionally, the digital business environment improves communication between enterprises and the government, enabling the government to better understand enterprise needs, further improving policy implementation efficiency, thus increasing the confidence and ability of enterprises to innovate (Hoskins & Carson, 2022; Scherrer & Perrig, 2021; Zafari et al., 2023). Lastly, smart contracts and blockchain technology improve the transparency and efficiency of policy implementation, reducing power-seeking behavior in policy subsidy processes and allowing equal access to innovation opportunities for all enterprises (Ozen & Ozturk-Kose, 2023).

A favorable business environment in a region or country generally leads to broader and more diverse market demand, providing greater opportunities for product and technological innovation (Mithani, 2023; L. Yu et al., 2023; Zafari et al., 2023). The digital business environment further optimises digital shopping patterns, driving the development of consumers' willingness and demand to buy (Karami et al., 2022). It also facilitates access to information about products and services, reducing information asymmetry between producers and consumers and increasing market competition efficiency (Varadarajan, 2020). Moreover, the digital business environment expands markets globally, expanding aggregate market demand. Finally, it enables firms to better understand consumer needs and preferences, offering more personalised products and services and creating conditions for lean innovation (Ghezzi & Cavallo, 2020; Karagiannis et al., 2022). In summary, the digital business environment can influence all aspects of market demand, reshaping market structures and business models.

The digital business environment strengthens competitive pressure in the market, pushing enterprises to improve their innovative strength and competitiveness. This promotes technological progress and upgrading of the entire industry (Ancillai et al., 2023; Do et al., 2022; Dong et al., 2023; Şimşek et al., 2022). Firstly, the digital business environment provides faster, more efficient and accurate data and information support, enhancing decision-making capabilities and operational efficiency, strengthening competitiveness (Helfat & Raubitschek, 2018; Nathan & Rosso, 2015). Secondly, it intensifies competition in the market, compelling enterprises to continuously innovate and optimise products, services and business models to maintain market advantages (Andersson & Xiao, 2016; Fini et al., 2023). The digital business environment impacts competitive pressure in three main ways: digitising and automating production processes, reducing R&D costs and risks, and conducting accurate and targeted marketing through various digital channels and tools (Giachetti

& Li Pira, 2022; Giachetti & Mensah, 2023). This results in improved production efficiency and quality, better understanding of market demand and trends, shorter product development cycles, and enhanced marketing effectiveness and customer conversion rates. In conclusion, the digital business environment necessitates digital transformation and innovation for companies to stay competitive in the market. Based on this analysis, we propose the research hypothesis:

Hypothesis: digital business environment has a significant positive impact on the innovation efficiency of ICT enterprises.

To test our research hypothesis, our research process is shown in Figure 1.

### 3. RESEARCH DESIGN

#### 3.1 Methodology

##### 3.1.1 ICT Industry Innovation Performance Evaluation Index System

The innovation efficiency of ICT enterprises in China was evaluated based on the “Enterprise Innovation Capability Evaluation Index System” developed by the Ministry of Science and Technology in 2013. To gather data on government subsidies, annual reports of enterprises were consulted, while information on tax concessions was obtained from the State Administration of Taxation’s proportion of tax concessions for high technology industries. The Doing Business Index was derived from the World Bank Doing Business Assessment Report. Total output value of high-tech industries and technology transactions were sourced from various statistical yearbooks, including China High-Tech Industry Statistical Yearbook, China Science and Technology Statistical Yearbook, and China Torch Statistical Yearbook. Data on digitization levels came from the China Digital Economy Development Report and the Digital China Index Report. An innovation performance evaluation index system was determined based on the specific characteristics of the ICT industry. This system was used to evaluate selected listed companies in the ICT sector, and Table 1 presents the details of the evaluation index system.

##### 3.1.2 Analytic Model of Innovation Performance of Listed ICT Companies Based on the Three-Stage DEA Model

The model developed by Charnes et al. (1978) is known as Data Envelopment Analysis (DEA), and it is a non-parametric method used for measuring the relative efficiency of decision-making units (DMUs). In the context of this study, the DMUs are ICT firms. In addition to the DEA model, the stochastic frontier model (SFA) introduced by Fried et al. (2002) was used in this study. SFA is a

Figure 1. Flow chart of the study

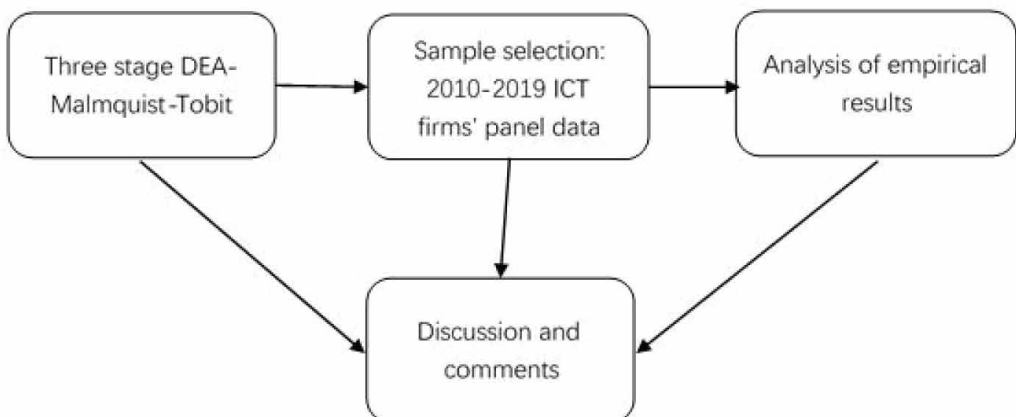


Table 1. Index system of innovation performance evaluation of listed ICT enterprises

1st Indicator	2nd Indicators	Measurement	Unit
Input	Funding	The proportion of R&D expenditure in operating income	%
	Manpower Input	The proportion of R&D employees	%
		Proportion of employees with graduate degree or above	%
Output	Patent	Number of patents applied	item
		Number of patents granted	item
	Transformation	Proportion of new product sales revenue	%
		Operating income growth rate	%
		Net profit	million
Environment	Policy	Government subsidy amount	million
		Tax incentive ratio	%
		Legal power protection index	12
	Financing	Get credit index	%
		Get credit index	%
	Technical	Total value of high-tech industry	million
		Technology transfer turnover	million
		Digital level (internet penetration)	%

parametric method used to estimate the technical inefficiency of firms and to identify the sources of inefficiency. The Malmquist index model was also used in this study to portray the dynamics of innovation efficiency changes in listed ICT firms. The Malmquist index measures the change in efficiency over time and identifies the sources of change. Finally, the Tobit model is used to analyze the impact of different factors on the innovation efficiency of ICT firms. The Tobit model is a regression model that takes into account censoring or truncation in the dependent variable. In the context of this study, the dependent variable is the measured innovation efficiency of each ICT firm. The BCC-DEA model is used to examine the relationship between innovation inputs and innovation performance in ICT firms. The analysis model was:  $\min \left[ \alpha - v \left( \sum_{i=1}^Z S_i^- + \sum_{j=1}^W S_j^+ \right) \right]$ , and the model had a non-Archimedes infinitesimal:

$$\begin{cases} \sum_{p=1}^n \lambda_p x_{ip} + S_i^- = \alpha x_{if}, i \in [1, Z] \\ s.t. \sum_{p=1}^n \lambda_p y_{jp} - S_j^+ = y_{jf}, j \in [1, W] \\ \sum_{p=1}^n \lambda_p = 1, p \in [1, n] \end{cases} \quad (1)$$

$\lambda_p, \alpha, S_i^-, S_j^+ \geq 0, p \in [1, n]$ ,  $x_{if}, y_{jf}$  respectively represent the  $i^{\text{th}}$  input and  $j^{\text{th}}$  output of the  $f^{\text{th}}$  DUM. Similarly,  $x_{ip}, y_{jp}$  represents the  $i^{\text{th}}$  input and  $j^{\text{th}}$  output of the  $p^{\text{th}}$  DUM;  $S_j^+$  is the remaining variable;  $S_i^-$  is slack variable;  $\lambda_p$  represents weight;  $v$  expressed as a non-Archimedean infinitesimal;

$\alpha$  is pure technical efficiency (PTE). Dividing comprehensive technical efficiency (TE) in BCC into PTE and scale technical efficiency (SE),  $TE=PTE \times SE$ , when  $TE=1$ , that is,  $PTE=1$ ,  $SE=1$ , which means that the input and output are optimal, and DMUs are effective.

The slack variables produced by the BCC model were mainly caused by environmental factors, management inefficiency or inefficiency, and statistical noise (Jin et al., 2023). Therefore, when constructing a similar SFA model to perform regression analysis on these variables, the slack variable was used as the dependent variable of the regression analysis, and the environmental variables and statistical noise (mixed error terms) were used as independent variables (Namasudra & Roy, 2018). Thus, the following random frontier model was constructed:

$$S_{mi} = f(p_i; \theta_m) + z_{mi} + v_{mi} \quad (2)$$

In this frontier model,  $i \in [1, j]$ ,  $m \in [1, k]$ ,  $S_{mi}$  denotes the slack of the  $m^{\text{th}}$  input in the  $i^{\text{th}}$  DMU,  $z_{mi} + v_{mi}$  represents the random error term;  $p_i, \theta_m$  respectively, represent the environmental variables and their coefficients.  $z_{mi}$  represents random statistical noise,  $v_{mi}$  is the management invalid, and  $z_{mi} \sim Q(0, \ell_{zm}^2)$ ;  $v_{mi} \sim Q^+(0, \ell_{vm}^2)$ . Finally, the initial original input variables were further adjusted, and all DMUs were placed under the same environmental conditions. The adjustment method was as follows:

$$X_{mi}^K = X_{mi} + [\max_i \{p_i \hat{\theta}^m\} - p_i \hat{\theta}^m] + [\max_i \{\hat{z}_{mi}\} - \hat{z}_{mi}] \quad (3)$$

$i \in [1, j]$ ,  $m \in [1, k]$ ,  $X_{mi}^K, X_{mi}$  indicate the investment after adjustment and before adjustment, respectively,  $\max_i \{p_i \hat{\theta}^m\} - p_i \hat{\theta}^m$  for the adjustment of environmental variables,  $\max_i \{\hat{z}_{mi}\} - \hat{z}_{mi}$  is to put all the DMUs in the same environment.

The output data from the adjusted DEA model and the original data are incorporated into the BCC model, which has variable returns to scale, in order to calculate the PTE, SE, TE, and efficiency values of the sampled ICT companies. By doing so, the DUMs' level of technical management can be accurately reflected while environmental and statistical noise is eliminated for increased accuracy. This multi-stage analysis allows for an assessment of which companies operate in optimal efficiency levels, and which require improvements to enhance productivity.

### 3.2 DEA-Malmquist Index Model

The Malmquist Index model is utilized to assess the productivity and efficiency of multiple DMUs over time, taking into account both technological progress and individual DMU performance changes. To better understand the dynamic evolution of innovation activities, this study employs the BCC-DEA-Malmquist analytical model. The distance functions formulated to evaluate inventions with varying returns to scale are provided below:

$$D_k(x^t, y^t) = \inf \left\{ \alpha : (x^t, y^t / \alpha) \in S^T(k) \right\} \quad (4)$$

$$S^t(k) = \left\{ x^t, y^t \mid x^t \geq \sum x^t \lambda, y^t \leq \sum y^t \lambda, \sum \lambda = 1, \lambda \geq 0 \right\} \quad (5)$$

In equation (4),  $x$  represents the input variable matrix,  $y$  represents the output variable matrix, and equation (5) represents the set of production possibilities with variable returns to scale in period  $t$ . From the equation, the function is greater than 1 if the output variable matrix is outside the production

possibility set; the function value is equal to 1 if the output variable matrix is at the boundary of the production possibility set; and the function value is less than 1 if the output variable matrix is within the production possibility set. therefore, the Malmquist index formula from period t to period t+1 is as follows:

$$M_k(x^t, y^t, x^{t+1}, y^{t+1}) = \left| \frac{D_k^t(x^{t+1}, y^{t+1})}{D_k^t(x^t, y^t)} \times \frac{D_k^{t+1}(x^{t+1}, y^{t+1})}{D_k^{t+1}(x^t, y^t)} \right|^{\frac{1}{2}} \quad (6)$$

Further Malmquist's exponential model in output terms is derived as:

$$M_k(x^t, y^t, x^{t+1}, y^{t+1}) = \frac{D_k^t(x^{t+1}, y^{t+1})}{D_k^t(x^t, y^t)} \quad (7)$$

where  $D_k^t(x^t, y^t)$  and  $D_k^{t+1}(x^{t+1}, y^{t+1})$  are the technical efficiency values for the two periods at the production point respectively; and  $D_k^t(x^{t+1}, y^{t+1})$  and  $D_k^{t+1}(x^t, y^t)$  are the technical efficiency values for the two periods during the mixing period according to the production point. Thus, equation (7) is further decomposed into:

$$M_k(x^t, y^t, x^{t+1}, y^{t+1}) = \left| \frac{D_k^t(x^{t+1}, y^{t+1})}{D_k^t(x^t, y^t)} \times \frac{D_k^{t+1}(x^{t+1}, y^{t+1})}{(D_k^{t+1})(x^t, y^t)} \right|^{\frac{1}{2}} = \frac{D_a^{t+1}(x^{t+1}, y^{t+1})}{D_a^t(x^t, y^t)} \left| \frac{D_a^t(x^{t+1}, y^{t+1})}{D_a^{t+1}(x^{t+1}, y^{t+1})} \right. \\ \left. \times \frac{D_a^t(x^t, y^t)}{(D_a^{t+1})(x^t, y^t)} \right|^{\frac{1}{2}} = \frac{D_b^{t+1}(x^{t+1}, y^{t+1})}{D_b^t(x^t, y^t)} \times \frac{D_a^{t+1}(x^{t+1}, y^{t+1})}{D_b^{t+1}(x^{t+1}, y^{t+1})} \left| \frac{D_a^t(x^{t+1}, y^{t+1})}{D_a^{t+1}(x^{t+1}, y^{t+1})} \times \frac{D_a^t(x^t, y^t)}{D_a^{t+1}(x^t, y^t)} \right|^{\frac{1}{2}} \\ \left. \times \frac{D_b^t(x^t, y^t)}{D_b^{t+1}(x^t, y^t)} \right|^{\frac{1}{2}} \quad (8)$$

In formula (8), pure efficiency change (PEC) is expressed as:

$$\frac{D_b^{t+1}(x^{t+1}, y^{t+1})}{D_b^t(x^t, y^t)}, \frac{D_a^{t+1}(x^{t+1}, y^{t+1})}{D_a^t(x^t, y^t)}$$

is expressed as scale efficiency change (SEC); and in the Malmquist index model, the product of pure efficiency change (PEC) and scale efficiency change (SEC) is the integrated technical change efficiency (EC), i.e.:

$$EC = PEC \times SEC, \left| \frac{D_a^t(x^{t+1}, y^{t+1})}{D_a^{t+1}(x^{t+1}, y^{t+1})} \times \frac{D_a^t(x^t, y^t)}{D_a^{t+1}(x^t, y^t)} \right|^{\frac{1}{2}}$$



denotes production technology progress TC, and TC is further decomposed into pure technical progress change, i.e.  $TC = PTC \times STC$ . Therefore, equation (8) can be simplified to:

$$MI = TFP = TC \times EC = PEC \times SEC \times PTC \times STC$$

which reflects total factor productivity progress.

$TFP$  indicates the change in the productivity of the DMU from period  $t$  to period  $t+1$ . If  $TFP > 1$ , it indicates an increase in the level of production, and vice versa.  $EC$  indicates the ratio between the actual output of the DMU and the theoretical maximum output, reflecting the ability of innovation to obtain maximum output;  $EC > 1$  indicates an increase in technical efficiency, and vice versa;  $TC > 1$  indicates technological progress and vice versa. In this paper,  $SEC$  indicates the scale of each company's input to innovation activities, i.e. whether the company's relevant funding and personnel are at the optimal scale;  $SEC > 1$  indicates optimised scale efficiency and vice versa;  $PEC$  indicates the rationality of each company's innovation input approach, structure and mechanism;  $PEC > 1$  indicates an increase in efficiency in technology use and vice versa.

## 4. ANALYSIS OF EMPIRICAL RESULTS

### 4.1 Sample Selection

The paper under consideration selected ICT companies listed on A-shares in China as the sample for examination during 2010-2019, as shown in Table 3. Since the DEA model necessitates all input and output indicators to be positive, some of the data in the sample had large values; thus, dimensionless pre-processing of the data was conducted using formula (9) to rescale the sample data into a positive interval. The formula (9) was applied to adjust the data and ensure the data sets were compliant with the DEA requirements. Unfortunately, without access to the actual formula, further elaboration on the process is not possible:

$$\begin{cases} Z_{ij} = 0.1 + \frac{x_{ij} - m_i}{M_i - m_i} \times 0.9 \\ m_i = \min(x_{i1}, x_{i2}, x_{i3}, \dots, x_{ij}) \\ M_i = \max(x_{i1}, x_{i2}, x_{i3}, \dots, x_{ij}) \end{cases} \quad (9)$$

where  $Z_{ij}$  represented the  $i$ th index of the  $j$ -th ICT industry listed company after the dimensionless treatment every year,  $m_i$  indicated the minimum value in the  $i$ -th index,  $M_i$  indicated the maximum value of the  $i$ -th index. After the above non-dimensional quantification preprocessing, it was ensured that all values belonged to  $[0.1, 1]$ , thus, ensuring the validity and accuracy of the DEA-Malmquist index model.

### 4.2 Analysis of Results Before Adjustment

#### 4.2.1 Analysis of Results Based on the First Stage BCC-DEA Model

In this study, the innovation efficiency of Chinese A-share listed ICT firms was evaluated using the investment-oriented CCR-BCC model in the DEAP 2.1 application software (available by contacting the authors due to journal space limitations). The results reveal that the integrated technical efficiency before adjustment has a mean value of 0.5614 and the pure technical efficiency is 0.8208. These

**Table 2. Descriptive statistics of input and output indicators**

Variables	Unit	Max	Min	Mean	SD
R&D employees	%	0.005	73.197	23.130	14.518
Graduate degree or above	%	0.001	2.910	0.240	4.992
R&D expenditure	%	0.007	21.778	6.595	41.928
Patents applied	items	9698	0	89.220	549.037
Patents granted	items	9711	0	74.870	548.883
New product sales revenue	%	1	0	0.1755	0.2541
Operating income growth rate	%	21.570	0	0.2304	0.983
Net profit	million	514800	-575100	13278.020	51977.110

findings suggest that the static technical efficiency and decomposition terms' mean values reflect the overall low innovation efficiency of Chinese ICT firms. Nonetheless, they also indicate that ICT listed firms have higher management levels and stronger operational capabilities in technological innovation and management. Additionally, according to the decomposition terms TE, PTE, and SE, the primary drivers of the ICT industry's development are management and investment in R&D personnel. Moreover, the scale effect has a more significant impact on low innovation efficiency. This finding suggests that the main reason for the low innovation efficiency of Chinese ICT enterprises is the lack of a scale advantage resulting from the industry's overall development.

#### *4.2.2 Analysis of Dynamic Innovation Efficiency of Listed Companies in ICT Industry*

The study utilized the Malmquist index to analyze changes in innovation efficiency for listed enterprises in the A-share ICT industry across different time periods (Table 3). Results indicated that Chinese ICT enterprises possess strong innovation capability, as evidenced by EC and TC values of 1.119 and 1.046, respectively, both greater than 1. Although the mean PTC value was 0.895, the SE change index remained above 1 throughout all time periods, indicating scale efficiency in the Chinese ICT industry. However, a decline in PTC was observed as the source of the drop in technical efficiency. The EC fell below 1 only in the period of 2014-2015, suggesting that the loss of TE during this time had a significant impact on the industry's innovation efficiency. In contrast, the M index decreased below 1 in 2017-2018, which indicates a slowdown in the growth of the Chinese ICT industry during this period. The low M index value can be attributed mainly to the limited level of PTE reflected in the low TC index. The study results, available upon request from the authors due to journal space constraints, showed only 20 companies (18% of sample size) with a Malmquist Index greater than 1. These findings suggest that, despite possessing high levels of management, Chinese ICT companies are unable to adequately improve their innovation efficiency through internal staff quality and that the industry's potential for growth is hindered by a scarcity of highly skilled human resources. Consequently, low innovation transformation efficiency remains a key factor impeding development in the Chinese ICT industry despite extensive collaboration between industry, academia, and research.

#### **4.3 Analysis of Results Based on SFA Model**

The study employed the slack variables of three input variables: the proportion of R&D personnel to enterprise employees, the proportion of employees holding postgraduate degrees or higher, and R&D expenditure investment. These were used as explanatory variables in constructing a SFA model (Devi et al., 2020; S. Lim & Zhu, 2016). The SFA utilized the total output value of the high-tech industry, the amount of technology transfer, and the level of digitization as explanatory variables. The effects of data and seven environmental variables on the three input slack variables were recalculated using

Table 3. Malmquist index and its decomposition

Period	EC	TC	PTC	STC	M index
2010-2011	1.191	0.962	0.823	1.420	1.248
2011-2012	1.031	1.055	0.924	1.222	1.222
2012-2013	1.079	1.066	0.947	1.298	1.383
2013-2014	1.176	1.076	0.902	1.262	1.431
2014-2015	0.885	1.210	1.073	1.052	1.100
2015-2016	1.358	0.917	0.745	1.262	1.229
2016-2017	1.107	1.213	0.952	1.192	1.454
2017-2018	1.090	0.953	0.857	1.114	0.983
2018-2019	1.157	0.971	0.832	1.035	1.319
Mean	1.119	1.046	0.895	1.206	1.263

Frontier 4.1 software (C. Guo & Zhu, 2017). Table 6 presents the results of the significance test for  $\lambda^2$  and  $\gamma$ , demonstrating that statistical noise (error) and environmental variables affect the analysis of the innovation efficiency of the sampled ICT-listed companies.

From a government perspective, the study's regression coefficients revealed that the slack variables of government subsidies and corporate R&D investment have positive coefficients, but only the R&D expenditure slack variable is significant. This suggests that government subsidies undermine firms' risk-taking and creativity while denying them the opportunity to develop their own independent creative talents (Fini et al., 2023; Ozen & Ozturk-Kose, 2023; F. Yu et al., 2023). Tax incentives have a positive effect on the slack variables of firms' R&D expenditure inputs, but the slack variables for both R&D staff and employee qualifications are negative. This indicates that tax incentives enhance the redundancy of a firm's R&D investment but reduce the redundancy of R&D personnel's investment (Dai & Chapman, 2022; Gross & Klein, 2022; He et al., 2022; Rosado-Cubero et al., 2023; J. Zhang & Guan, 2018). Overall, this demonstrates that tax policy is more steering than subsidizing. The variables of access to investment and credit slack both produced negative regression results, emphasizing the financing environment's positive effect on firms' innovation efficiency (Alquist et al., 2022; Cull & Xu, 2005; Ribeiro & Shapira, 2020). Access to capital is an important factor in reducing firms' barriers to innovating, and financing institutions increase innovation effectiveness by reducing firms' costs of innovation while monitoring innovation-related actions of innovation agents (Long & Pelloni, 2017; Ribeiro & Shapira, 2020). The regression coefficients for both the slack in the input variable and the legal power protection index are negative, indicating that the redundancy of the input variable decreases with improved legal power protection. For a long time, imperfections in the Chinese market system have led to a lack of effective protection of firms' legal rights (especially intellectual property rights), resulting in serious violations of the legal rights of firms investing in China, at the expense of their willingness to innovate.

From a market perspective, the level of digitization and marketization can significantly impact ICT companies' investment in innovation (Boudreau et al., 2022). The regression analysis shows that R&D investment and R&D staff quality are negatively affected by the degree of digitization, but positively impacted by slack in R&D staff. This indicates that increasing digitization leads to greater information transparency, which can make some R&D personnel redundant, while lowering the redundancy of corporate R&D expenditures and highly qualified R&D staff. This is because increased digitization allows for lean innovation and an open innovation paradigm, which are crucial for enhancing firms' innovation performance and quality (Li et al., 2023; Miric et al., 2019). Moreover, the regression results based on high-tech industries' gross value indicate that as

industry growth increases, the redundancy of firms' R&D inputs reduces, while the redundancy of human resources increases. This is due to the larger innovation technology base created as the industry grows, leading to lower costs of enterprise innovation (Andries et al., 2021; Khan et al., 2022; Moshirian et al., 2021; Neumann et al., 2019). However, this can also lead to talent clustering and human resource redundancy. The regression results for both technology transfer efficiency and firm innovation input slack variables show a negative correlation, implying that higher technology transfer turnover rates can significantly reduce the redundancy of firms' innovation resource inputs (Fareed et al., 2022; Z. Jia et al., 2023). Therefore, the development of technology markets can help decrease redundancies in firms' innovation resource inputs and enhance their innovation quality.

#### 4.4 Analysis of the Adjusted Results

The first stage of efficiency measurement included environmental factors and statistical noise, which impacted the accuracy of measuring the true innovation efficiency of ICT listed companies. Therefore, further adjustments were necessary using DEAP 2.1 software in the second stage, where technical efficiency, pure technical efficiency, and scale efficiency were recalculated with adjusted input variables and original output variables. The adjusted results (available from the authors due to journal space constraints) demonstrate significant improvements in technical efficiency, pure technical efficiency, and scale efficiency after removing environmental variables and statistical

Table 4. SFA regression results of innovation efficiency of the sampled

	R&D Expenditure	R&D Employees	Degree
Constant Term	4.68*** (1.20)	4.17*** (1.01)	3.68*** (1.15)
Government Subsidies	0.74** (0.36)	1.36 (1.06)	0.75 (1.33)
Tax Incentive	2.36*** (0.61)	-0.96 (1.03)	-0.92 (0.96)
Legal Rights	-0.58*** (0.11)	-1.67** (0.84)	-1.35*** (0.24)
Get Credit	-1.59** (0.69)	-1.32*** (0.36)	-0.20 (0.97)
Get Investment	-2.56*** (0.20)	-1.36*** (0.42)	-2.19*** (0.72)
Total Value	-1.28** (0.64)	1.11*** (0.39)	2.18*** (0.68)
Technology Transfer	-2.37*** (0.36)	-1.32*** (0.48)	-1.13*** (0.41)
Digitalization	-1.59** (0.60)	1.99** (0.98)	-1.79*** (0.62)
Log	-402.39	-398.69	-542.09
LR	1.77***	2.03***	4.27***

Note: \*, \*\*, \*\*\* denote significant at the level of 0.1, 0.05, and 0.001, respectively, and the standard deviation in parentheses

noise. The mean values for technical efficiency, pure technical efficiency, and scale efficiency are 0.747, 0.814, and 0.861, respectively, compared to pre-adjustment mean values of 0.561, 0.821, and 0.708.

Interestingly, technical efficiency and scale efficiency improved more significantly after adjustment, while pure technical efficiency showed a downward trend. Previously, Chinese ICT-listed companies' innovation performance was mainly driven by pure technical efficiency, representing management level. However, after adjustment, technical efficiency and scale efficiency have become increasingly important drivers of overall efficiency. Removing environmental variables resulted in a significant improvement in the overall innovation efficiency of enterprises. This confirms that the adjusted values of each efficiency accurately reflect the level of innovation efficiency of listed ICT enterprises. Moreover, this demonstrates the important influence of business environment elements on firms' innovation performance.

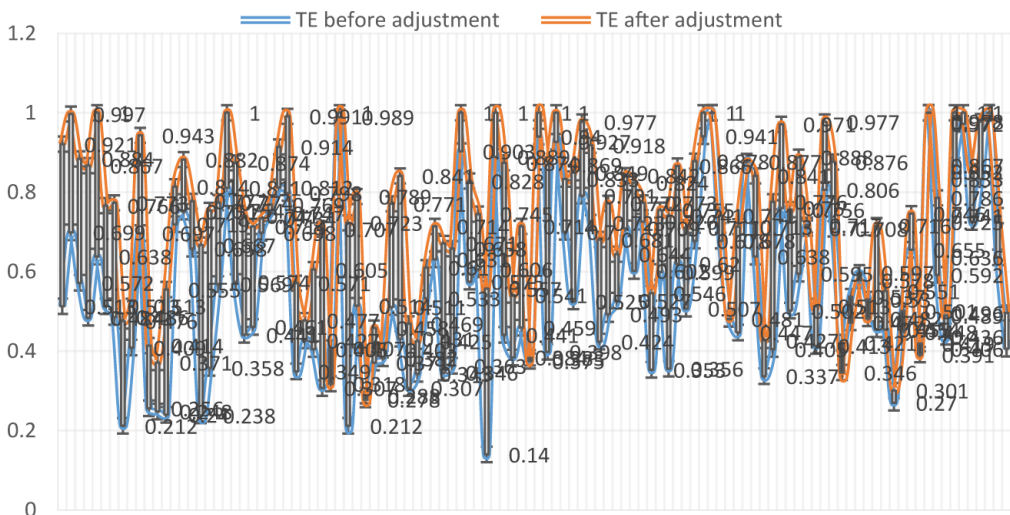
#### 4.4.1 Analysis of TE of the Sampled Listed ICT Companies

Figure 1 illustrates the significant improvement in the technical efficiency of ICT listed enterprises after removing external influences, with the value increasing from 0.561 to 0.747 compared to the pre-adjustment period. The number of businesses on the cutting edge of technological efficiency also increased from three before adjustment to thirteen after adjustment, indicating that the optimization of the business environment has enabled better distribution of innovation resources and allowed companies to fully leverage their technological advantages. Moreover, after excluding external environmental influences and statistical noise, the total technical efficiency of ICT firms experienced substantial growth, indicating that the improved business climate has positively impacted the development of China's ICT industry. This highlights the importance of optimizing the business environment for promoting innovation and improving the efficiency of firms in the industry.

#### 4.4.2 Analysis of PTE of the Listed ICT Companies

Figure 2 displays the PTE before and after adjustment. The adjustment resulted in an increase in the number of businesses with a PTE of 1, from 8 to 32, which equates to an increase from 7.27% to 29.09%. However, the overall reduction in PTE raises concerns that environmental influences and

Figure 2. Comparison of technical efficiency before and after adjustment



statistical noise may have exaggerated the beneficial effects of PTE on enterprises' overall innovation efficiency. This is because statistical analysis often fails to consider the impact of environmental factors and attributes increases in firm efficiency and innovation performance solely to increased management, which differs from reality.

#### 4.4.3 Analysis of SE of Listed ICT Companies

Figure 3 presents the changes in scale efficiency of listed ICT companies before and after adjustment. The results show that the scale efficiency increased from 0.708 to 0.861, an increase of around 16%. The statistical analysis also indicates that scale efficiency increased by 90 companies before and after adjustment. This suggests that the scale effect of listed companies in the ICT industry is improving, and the industry as a whole is becoming stronger. While some companies experienced a decline in scale efficiency, the most affected were core business and chip-related companies due to the business environment. However, enterprises on the frontier side of scale efficiency were not impacted, indicating that the level of a company's own development plays a significant role in its ability to respond to changes in the business environment. This demonstrates that firms with stronger capabilities are less susceptible to changes in the country's business environment.

### 4.5 The Influencing Factors of Innovation Performance

#### 4.5.1 Analysis Model

Based on the literature review and research hypotheses, the DEA model results are used as dependent variables. Since the DEA model results fall within the [0,1] interval, technical efficiency, pure technical efficiency, and scale efficiency are used as dependent variables. By combining input elements and environmental elements and applying Tobit regression analysis, the impact of various elements of the business environment on the innovation performance of ICT companies is verified through the following model:

Model 1:

Figure 3. Comparison before and after adjustment of PTE

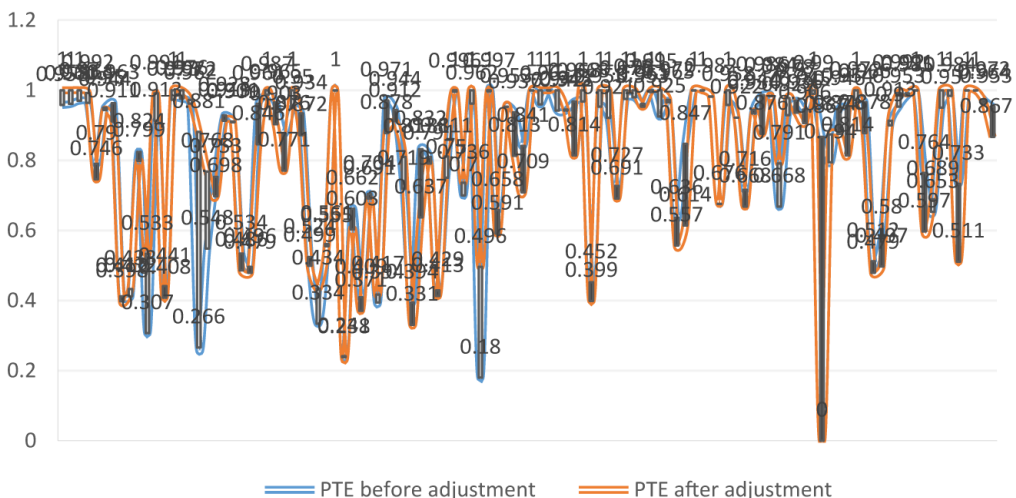
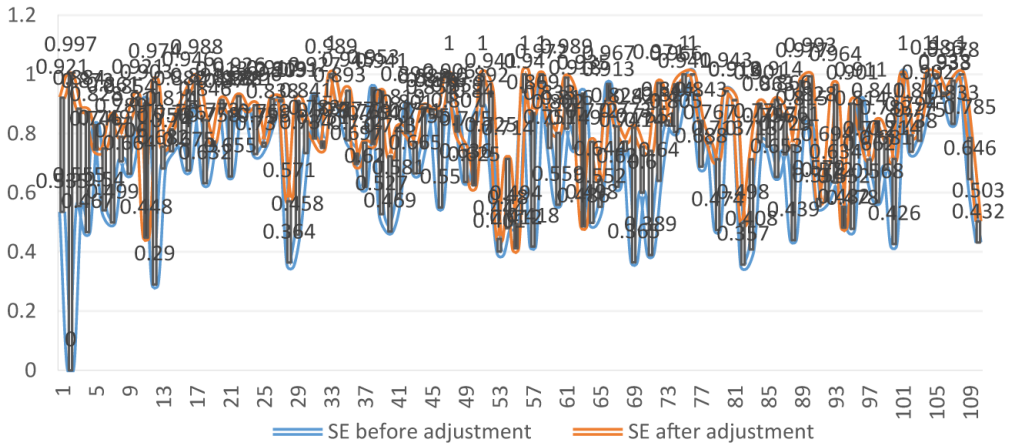


Figure 4. Comparison before and after scale efficiency adjustment



$$\begin{aligned}
 Crste_{it} = & \chi_0 + \chi_1 R \& Dinvestment_{it} + \chi_2 R \& Dpersonnel_{it} + \chi_3 postgraduate_{it} \\
 & + \chi_4 subsidy + \chi_5 tax_{it} + \chi_6 protect + \chi_7 loan_{it} + \chi_8 investment_{it} + \chi_9 vhtech_{it} \\
 & + \chi_{10} techtransfer + \chi_{11} digitization_{it} + \sigma_{it}
 \end{aligned} \tag{10}$$

Model 2:

$$\begin{aligned}
 Vrste_{it} = & \alpha_0 + \alpha_1 R \& Dinvestment_{it} + \alpha_2 R \& Dpersonnel_{it} + \alpha_3 postgraduate_{it} \\
 & + \alpha_4 subsidy + \alpha_5 tax_{it} + \alpha_6 protect + \alpha_7 loan_{it} + \alpha_8 investment_{it} + \alpha_9 vhtech_{it} \\
 & + \alpha_{10} techtransfer + \alpha_{11} digitization_{it} + \eta_{it}
 \end{aligned} \tag{11}$$

Model 3:

$$\begin{aligned}
 Scale_{it} = & \beta_0 + \beta_1 R \& Dinvestment_{it} + \beta_2 R \& Dpersonnel_{it} + \beta_3 postgraduate_{it} \\
 & + \beta_4 subsidy + \beta_5 tax_{it} + \beta_6 protect + \beta_7 loan_{it} + \beta_8 investment_{it} + \beta_9 vhtech_{it} \\
 & + \beta_{10} techtransfer + \beta_{11} digitization_{it} + \xi_{it}
 \end{aligned} \tag{12}$$

Among them,  $Crste$ ,  $Vrste$ ,  $Scale$  respectively represent the comprehensive technical efficiency, pure technical efficiency and scale effect previously calculated by DEA model,  $\chi, \alpha, \beta$  is the parameter to be estimated, subscript  $i$  means the  $i$ -th enterprise,  $t$  means year  $t$ ,  $\sigma, \eta, \xi$  is the random interference term. Indicators and explanations are shown in Table 5.

Among them, because the World Bank's evaluation standards use the two cities of Beijing and Shanghai as survey samples for data analysis, the standards for the policy environment and investment environment are also conducted in accordance with the standards of Beijing and Shanghai to reduce statistical errors.

Table 5. Descriptive statistics and interpretation of each indicator

Variable	Measurement	Sample	Min	Max	Mean	SD
<b>R&amp;D Personnel</b>	R&D employees(%)	110	0.005	73.197	23.130	14.518
<b>R&amp;D Investment</b>	Degree (%)	110	0.007	21.778	6.595	41.928
<b>Postgraduate</b>	R&D expenditure (%)	110	0.001	2.910	0.240	4.992
<b>Subsidy</b>	Amount of government subsidy (RMB million)	110	30.585	2233489.051	3828.779	21406.173
<b>Tax</b>	Tax credit ratio (%)	10	0	15	8.494	6.863
<b>Protect</b>	Legal Protection (%)	10	1	5	3.647	1.328
<b>Loan</b>	Credit Index (%)	10	15	60	36.584	41.256
<b>Investment</b>	Investment indices (%)	10	20	70	39.157	36.556
<b>Value H-Tech</b>	Total value of high technology industries (RMB million)	10	604300000	1854060000	1205440000	1303.245
<b>Tech Transfer</b>	Technology Transfer Turnover (RMB million)	10	22260000	176974000	80709450	4538.986
<b>Digitization</b>	Digitalisation index (%)	10	10.654	76.286	42.873	19.796

#### 4.5.2 Result Analysis

The study conducted a Tobit analysis using stata15.1 to examine the factors affecting innovation efficiency in the ICT industry. The empirical results are presented in Table 6, which show that both internal input elements, such as R&D investment and quality of R&D staff, and external environmental factors, such as institutions, funding, and markets, have a positive impact on all three models. Model 1 highlights that R&D spending has the greatest positive incentive effect on technical efficacy, indicating that companies are the primary source of innovation. Additionally, the importance of investment is second only to R&D spending, suggesting that financial restraints can stifle innovation. The impact of tax incentives on advancing technical efficacy is found to be minimal.

In Model 2, government subsidies negatively influence pure technical efficiency by creating an imbalance in innovation costs between subsidized and non-subsidized firms, resulting in reduced quality of business management (Hu et al., 2019). Similarly, reliance on the government lowers the management team's capability, negatively affecting the company's ability to generate profits (Gutub, n.d.). However, the legal power protection index positively incentivizes purely technological efficiency since it protects IP rights for ICT enterprises.

In Model 3, government subsidies, legal power protection, and levels of digitalization have a negative effect on scale efficiency. Government subsidies deter innovation since firms only innovate to receive subsidies, causing a mismatch between firms and reduced investment in other innovations (Ding et al., 2022; D. Guo et al., 2022; C. Y. Lim et al., 2018). Digitalization also causes a mismatch between firms, with small and medium-sized businesses avoiding innovation to avoid competing with bigger businesses, reducing the effectiveness of scale. Investment is the biggest inducement to scale efficiency in ICT enterprises, mainly because it lowers the risk of failure and encourages consistent and scientific analysis of the firm's innovation initiatives by investors (Contractor et al., 2020; Long & Pelloni, 2017; Teece, 2018).

Overall, the study identifies several factors that positively and negatively affect innovation efficiency in the ICT industry, including internal input elements, external environmental factors, government subsidies, legal power protection, and digitalization.



**Table 6. Tobit model analysis results of factors influencing innovation efficiency of ICT enterprises**

Influencing factors	Model 1	Model2	Model 3
R&D personnel	0.94E+89**	0.52E+11**	0.97E+34*
R&D investment	0.45E+16**	0.22E+88	0.63E+15*
Postgraduate	0.14E+49**	0.25E+72**	0.08E+25
Subsidy	0.57E+55**	-0.12E+34*	-0.46E+44**
Tax	0.35E+94	1.66E+33	+0.65E+80
Protect	0.73E+73***	0.96E+88**	-0.18E+32**
Loan	0.36E+16*	0.23E+11***	0.21E+22**
Investment	0.75E+79***	0.43E+55**	0.99E+73**
VHtech	0.12E+76**	-1.32E+66*	0.82E+72*
Techtransfer	0.68E+35**	-0.25E+34**	0.67E+44**
Digitization	0.87E+58***	0.11E+00**	-0.83e+18
Log likelihood	81.64831532	22.58513643	63.53466492
Wald chi2 (11)	68.36	53.19	47.38
Prob>chin2	0.0000	0.0000	0.0003

Note: \*, \*\*, \*\*\* indicate significant levels at 0.1, 0.05, and 0.001, respectively

## 5. DISCUSSION

The study's results suggest that although government subsidies can provide a boost to the ICT industry, they can also create imbalances and market monopolies that stifle innovation. Additionally, the lack of high-end human capital and low corporate management efficiency are significant barriers to innovation development in the industry. To address these issues, it is necessary to focus on developing a more diverse and inclusive talent pipeline and improving corporate management practices. It is also important to prioritize innovation development across the entire industry, rather than solely focusing on leading enterprises or those receiving government subsidies. By doing so, the industry can move towards a more balanced and sustainable innovation ecosystem that benefits all stakeholders.

### 5.1 Theoretical Implications

Environmental factors have a significant impact on the innovation efficiency of ICT firms, demonstrating that the business environment plays a vital role in firms' innovation strategies (Neumann et al., 2019; Prajogo, 2016; Varriale et al., 2021). As the business environment continues to be optimized, it becomes increasingly crucial in driving corporate innovation and technological progress (Andreeva et al., 2021; Khan et al., 2020; Möller et al., 2020). However, while the policy environment can facilitate this optimization, its impact on the business environment's role is not always positive (Khan et al., 2021; Qiang et al., 2021; Reyes et al., 2021; Vo et al., 2020). Although previous studies have primarily focused on optimizing individual elements of the business environment, recent research has emphasized the selection of regional innovation strategies based on the overall business environment (Contractor et al., 2020; Gaganis et al., 2019; Prajogo, 2016; Wong et al., 2021). In line with this new trend, our study examines how various business environment indicators impact firms' investment in innovation to provide a theoretical framework for improving innovation efficiency.

Given the complex and subjective nature of the business environment, quantifying its impact on firms' investment in innovation is challenging. Previous research has highlighted the government's leadership role in providing effective policy guidance, but with the rapid expansion of the internet

economy, variables related to firms' perceived returns have become increasingly important in encouraging them to innovate (Bai et al., 2019; Chakravarty, 2022; S.-S. Chen et al., 2021; Khan et al., 2023; X. Wang et al., 2019). Our paper analyzes the specific extent to which different factors contribute to firms' investment in innovation, emphasizing the stimulating effect of the policy environment on their investment. This analysis provides theoretical guidance for creating a business climate that encourages firms to invest in innovation and improve their innovation efficiency.

## **5.2 Practical Implications**

The findings of this paper offer valuable insights for optimizing the business environment and enhancing enterprise innovation efficiency. At the government level, differentiated guidance policies should be implemented to cultivate innovation growth poles for enterprises of different gradients fairly. Policy support should be given to enterprises with strong innovation capabilities but lagging behind in development while assisting leading enterprises in improving their innovation mechanisms. Selecting and nurturing unicorn enterprises with innovative capabilities can establish a reasonable innovation gradient in the ICT industry. Establishing an innovation cooperation mechanism can take advantage of high-gradient enterprises' driving effect on low-gradient enterprises. The government should also use policy instruments to establish a sound industry-university-research cooperation alliance and encourage universities to improve ICT technology research and development and management-related talent training.

Enterprises can actively seek institutional dividends conducive to their development by enhancing their organizational structure and operational mechanisms. They can further develop niche markets and ensure core competitiveness in these markets. SMEs can improve their innovation efficiency through collaboration with large enterprises to enhance production methods and technologies, thus increasing the market competitiveness of their products. By training and enhancing the overall staffing level of enterprises, especially the R&D capabilities of core ICT technicians and the management level of professional managers, they can improve their innovation efficiency. It is essential to adapt innovation strategies to the business environment and enhance the efficiency of innovation commercialization.

## **5.3 Limitations and Future Research**

This study has several limitations that provide a starting point for further research. Firstly, it is challenging to generalize about the complexity of the business environment solely from policy, investment, and market data while ignoring differences between cities and countries. The results of this study may vary depending on resource endowments and cultural values. Future research in other developing countries and cities is necessary to confirm these findings. Secondly, although our study focused on the homogeneous economic environment in mainland China due to strong central government coordination, the sample size limitations of our available data survey could affect our results' accuracy. Additionally, only listed companies were examined, limiting our ability to monitor the consequences for unlisted start-ups adequately. Future research will aim to expand the range of organizations assessed and identify potential confounding factors at a regional level that may distort our findings. Finally, the business environment in a region changes with both formal and informal institutions, thereby impacting the efficiency of business innovation. Therefore, continuous optimization of the business environment remains an essential topic, particularly in emerging economies.

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## REFERENCES

- Alquist, R., Chabot, B. R., & Yamarthy, R. (2022). The price of property rights: Institutions, finance, and economic growth. *Journal of International Economics*, *137*, 103594. doi:10.1016/j.jinteco.2022.103594
- Amouri, A., Festa, G., Shams, S. M. R., Sakka, G., & Rossi, M. (2021). Technological propensity, financial constraints, and entrepreneurial limits in young entrepreneurs' social business enterprises: The tunisian experience. *Technological Forecasting and Social Change*, *173*, 121126. doi:10.1016/j.techfore.2021.121126
- Ancillai, C., Sabatini, A., Gatti, M., & Perna, A. (2023). Digital technology and business model innovation: A systematic literature review and future research agenda. *Technological Forecasting and Social Change*, *188*, 122307. doi:10.1016/j.techfore.2022.122307
- Andersson, M., & Xiao, J. (2016). Acquisitions of start-ups by incumbent businesses: A market selection process of "high-quality" entrants? *Research Policy*, *45*(1), 272–290. doi:10.1016/j.respol.2015.10.002
- Andreeva, T., Garanina, T., Sáenz, J., Aramburu, N., & Kianto, A. (2021). Does country environment matter in the relationship between intellectual capital and innovation performance? *Journal of Business Research*, *136*, 263–273. doi:10.1016/j.jbusres.2021.07.038
- Andries, P., Clarysse, B., & Costa, S. (2021). Technology ventures' engagement of external actors in the search for viable market applications: On the relevance of Technology Broadcasting and Systematic Validation. *Journal of Business Venturing*, *36*(6), 106145. doi:10.1016/j.jbusvent.2021.106145
- Bai, Y., Song, S., Jiao, J., & Yang, R. (2019). The impacts of government R&D subsidies on green innovation: Evidence from Chinese energy-intensive firms. *Journal of Cleaner Production*, *233*, 819–829. doi:10.1016/j.jclepro.2019.06.107
- Boateng, E., Agbola, F. W., & Mahmood, A. (2021). Foreign aid volatility and economic growth in Sub-Saharan Africa: Does institutional quality matter? *Economic Modelling*, *96*, 111–127. doi:10.1016/j.econmod.2020.12.032
- Böttcher, T. P., Weking, J., Hein, A., Böhm, M., & Krcmar, H. (2022). Pathways to digital business models: The connection of sensing and seizing in business model innovation. *The Journal of Strategic Information Systems*, *31*(4), 101742. doi:10.1016/j.jsis.2022.101742
- Boudreau, K. J., Jeppesen, L. B., & Miric, M. (2022). Profiting from digital innovation: Patents, copyright and performance. *Research Policy*, *51*(5), 104477. doi:10.1016/j.respol.2022.104477
- Brousseau, E., Garrouste, P., & Raynaud, E. (2011). Institutional changes: Alternative theories and consequences for institutional design. *Journal of Economic Behavior & Organization*, *79*(1), 3–19. doi:10.1016/j.jebo.2011.01.024
- Chakravarty, S. (2022). Resource constrained innovation in a technology intensive sector: Frugal medical devices from manufacturing firms in South Africa. *Technovation*, *112*, 102397. doi:10.1016/j.technovation.2021.102397
- Chang, P.-L., & Chen, Y. (2021). Informal institutions and comparative advantage of South-based MNEs: Theory and evidence. *Journal of Development Economics*, *148*, 102566. doi:10.1016/j.jdeveco.2020.102566
- Charnes, A., Cooper, W. W., & Rhodes, E. (1978). Measuring the efficiency of decision making units. *European Journal of Operational Research*, *2*(6), 429–444. doi:10.1016/0377-2217(78)90138-8
- Chen, H., & Tian, Z. (2022). Environmental uncertainty, resource orchestration and digital transformation: A fuzzy-set QCA approach. *Journal of Business Research*, *139*, 184–193. doi:10.1016/j.jbusres.2021.09.048
- Chen, S.-S., Kao, W.-C., & Wang, Y. (2021). Tax policy and innovation performance: Evidence from enactment of the alternative simplified credit. *Journal of Banking & Finance*, *125*, 106081. doi:10.1016/j.jbankfin.2021.106081
- Chen, Z. (2022). Research on Internet Security Situation Awareness Prediction Technology Based on Improved RBF Neural Network Algorithm. *Journal of Computational and Cognitive Engineering*, *1*(3), 103–108. doi:10.47852/bonviewJCCE149145205514
- Choi, D. Y., & Perez, A. (2007). Online piracy, innovation, and legitimate business models. *Technovation*, *27*(4), 168–178. doi:10.1016/j.technovation.2006.09.004

- Choi, K. H., & Kwon, G. H. (2023). Strategies for sensing innovation opportunities in smart grids: In the perspective of interactive relationships between science, technology, and business. *Technological Forecasting and Social Change, 187*, 122210. doi:10.1016/j.techfore.2022.122210
- Contractor, F. J., Dangol, R., Nuruzzaman, N., & Raghunath, S. (2020). How do country regulations and business environment impact foreign direct investment (FDI) inflows? *International Business Review, 29*(2), 101640. doi:10.1016/j.ibusrev.2019.101640
- Cull, R., & Xu, L. C. (2005). Institutions, ownership, and finance: The determinants of profit reinvestment among Chinese firms. *Journal of Financial Economics, 77*(1), 117–146. doi:10.1016/j.jfineco.2004.05.010
- Dahabiyeh, L., & Constantinides, P. (2022). Legitimizing digital technologies in industry exchange fields: The case of digital signatures. *Information and Organization, 32*(1), 100392. doi:10.1016/j.infoandorg.2022.100392
- Dai, X., & Chapman, G. (2022). R&D tax incentives and innovation: Examining the role of programme design in China. *Technovation, 113*, 102419. doi:10.1016/j.technovation.2021.102419
- Delorme, D. (2023). The role of proximity in the design of innovation intermediaries' business models. *Technological Forecasting and Social Change, 188*, 122246. doi:10.1016/j.techfore.2022.122246
- Devi, D., Namasudra, S., & Kadry, S. (2020). A Boosting-Aided Adaptive Cluster-Based Undersampling Approach for Treatment of Class Imbalance Problem. *International Journal of Data Warehousing and Mining, 16*(3), 60–86. doi:10.4018/IJDWM.2020070104
- Ding, J., Liu, B., & Shao, X. (2022). Spatial effects of industrial synergistic agglomeration and regional green development efficiency: Evidence from China. *Energy Economics, 112*, 106156. doi:10.1016/j.eneco.2022.106156
- Ding, J., Wang, J., Liu, B., & Peng, L. (2022). 'Guidance' or 'Misleading'? The government subsidy and the choice of enterprise innovation strategy. *Frontiers in Psychology, 13*, 1005563. <https://www.frontiersin.org/articles/10.3389/fpsyg.2022.1005563>. doi:10.3389/fpsyg.2022.1005563 PMID:36267081
- Do, Q., Mishra, N., Colicchia, C., Creazza, A., & Ramudhin, A. (2022). An extended institutional theory perspective on the adoption of circular economy practices: Insights from the seafood industry. *International Journal of Production Economics, 247*, 108400. doi:10.1016/j.ijpe.2021.108400
- Dong, C., Zhang, Y., Li, Y., Lee, E., & Chen, L. (2023). What makes nonprofit organizations (NPOs) talk transparently about their connections with businesses on Twitter? Insights from nonprofit-business network portfolios and resource dependencies. *Public Relations Review, 49*(2), 102314. doi:10.1016/j.pubrev.2023.102314
- Fareed, Z., Abbas, S., Madureira, L., & Wang, Z. (2022). Green stocks, crypto asset, crude oil and COVID19 pandemic: Application of rolling window multiple correlation. *Resources Policy, 79*, 102965. doi:10.1016/j.resourpol.2022.102965 PMID:36068839
- Fini, R., Perkmann, M., Kenney, M., & Maki, K. M. (2023). Are public subsidies effective for university spinoffs? Evidence from SBIR awards in the University of California system. *Research Policy, 52*(1), 104662. doi:10.1016/j.respol.2022.104662
- Fried, H. O., Lovell, C. A. K., Schmidt, S. S., & Yaisawarng, S. (2002). Accounting for Environmental Effects and Statistical Noise in Data Envelopment Analysis. *Journal of Productivity Analysis, 17*(1), 157–174. doi:10.1023/A:1013548723393
- Gaganis, C., Pasiouras, F., & Voulgari, F. (2019). Culture, business environment and SMEs' profitability: Evidence from European Countries. *Economic Modelling, 78*, 275–292. doi:10.1016/j.econmod.2018.09.023
- Ghezzi, A., & Cavallo, A. (2020). Agile Business Model Innovation in Digital Entrepreneurship: Lean Startup Approaches. *Journal of Business Research, 110*, 519–537. doi:10.1016/j.jbusres.2018.06.013
- Ghosh, S., Hughes, M., Hodgkinson, I., & Hughes, P. (2021). Digital transformation of industrial businesses: A dynamic capability approach. *Technovation, 102414*. doi:10.1016/j.technovation.2021.102414
- Giachetti, C., & Li Pira, S. (2022). Catching up with the market leader: Does it pay to rapidly imitate its innovations? *Research Policy, 51*(5), 104505. doi:10.1016/j.respol.2022.104505
- Giachetti, C., & Mensah, D. T. (2023). Catching-up during technological windows of opportunity: An industry product categories perspective. *Research Policy, 52*(2), 104677. doi:10.1016/j.respol.2022.104677

- Gross, T., & Klein, P. (2022). Optimal tax policy and endogenous growth through innovation. *Journal of Public Economics*, 209, 104645. doi:10.1016/j.jpubeco.2022.104645
- Guo, C., & Zhu, J. (2017). Non-cooperative two-stage network DEA model: Linear vs. parametric linear. *European Journal of Operational Research*, 258(1), 398–400. doi:10.1016/j.ejor.2016.11.039
- Guo, D., Guo, Y., & Jiang, K. (2022). Government R&D support and firms' access to external financing: Funding effects, certification effects, or both? *Technovation*, 115, 102469. doi:10.1016/j.technovation.2022.102469
- Gutub, A. (n.d.). *Boosting image watermarking authenticity spreading secrecy from counting-based secret-sharing*. CAAI Transactions on Intelligence Technology. 10.1049/cit2.12093
- He, E., Jacob, M., Vashishtha, R., & Venkatachalam, M. (2022). Does differential taxation of short-term relative to long-term capital gains affect long-term investment? *Journal of Accounting and Economics*, 101479(1), 101479. doi:10.1016/j.jacceco.2022.101479
- Helfat, C. E., & Raubitschek, R. S. (2018). Dynamic and integrative capabilities for profiting from innovation in digital platform-based ecosystems. *Research Policy*, 47(8), 1391–1399. doi:10.1016/j.respol.2018.01.019
- Hoskins, J. D., & Carson, S. J. (2022). Industry conditions, market share, and the firm's ability to derive business-line profitability from diverse technological portfolios. *Journal of Business Research*, 149, 178–192. doi:10.1016/j.jbusres.2022.05.026
- Hu, J., Jiang, H., & Holmes, M. (2019). Government subsidies and corporate investment efficiency: Evidence from China. *Emerging Markets Review*, 41, 100658. doi:10.1016/j.ememar.2019.100658
- Jia, Y., Su, J., Cui, L., Wu, L., & Hua Tan, K. (2023). Platform business model innovation in the digitalization era: A “driver-process-result” perspective. *Journal of Business Research*, 160, 113818. doi:10.1016/j.jbusres.2023.113818
- Jia, Z., Tiwari, S., Zhou, J., Farooq, M. U., & Fareed, Z. (2023). Asymmetric nexus between Bitcoin, gold resources and stock market returns: Novel findings from quantile estimates. *Resources Policy*, 81, 103405. doi:10.1016/j.resourpol.2023.103405
- Jiang, Y., Yan, X., Yang, Z., & Subramanian, U. (2023). Returnee employees or independent innovation? The innovation strategy of latecomer countries: Evidence from high-tech enterprises in China. *Technological Forecasting and Social Change*, 192, 122591. doi:10.1016/j.techfore.2023.122591
- Jin, F., Cai, Y., Zhou, L., & Ding, T. (2023). Regret-rejoice two-stage multiplicative DEA models-driven cross-efficiency evaluation with probabilistic linguistic information. *Omega*, 117, 102839. doi:10.1016/j.omega.2023.102839
- Karagiannis, D., Buchmann, R. A., & Utz, W. (2022). The OMiLAB Digital Innovation environment: Agile conceptual models to bridge business value with Digital and Physical Twins for Product-Service Systems development. *Computers in Industry*, 138, 103631. doi:10.1016/j.compind.2022.103631
- Karami, M., Baber, W. W., & Ojala, A. (2022). The effectual process of business model innovation for seizing opportunities in frontier markets. *Technovation*, 117, 102595. doi:10.1016/j.technovation.2022.102595
- Khan, Z., Ali, S., Dong, K., & Li, R. Y. M. (2021). How does fiscal decentralization affect CO2 emissions? The roles of institutions and human capital. *Energy Economics*, 94, 105060. doi:10.1016/j.eneco.2020.105060
- Khan, Z., Badeeb, R. A., & Nawaz, K. (2022). Natural resources and economic performance: Evaluating the role of political risk and renewable energy consumption. *Resources Policy*, 78, 102890. doi:10.1016/j.resourpol.2022.102890
- Khan, Z., Hossain, M. R., Badeeb, R. A., & Zhang, C. (2023). Aggregate and disaggregate impact of natural resources on economic performance: Role of green growth and human capital. *Resources Policy*, 80, 103103. doi:10.1016/j.resourpol.2022.103103
- Khan, Z., Hussain, M., Shahbaz, M., Yang, S., & Jiao, Z. (2020). Natural resource abundance, technological innovation, and human capital nexus with financial development: A case study of China. *Resources Policy*, 65, 101585. doi:10.1016/j.resourpol.2020.101585

- Kraus, S., Durst, S., Ferreira, J. J., Veiga, P., Kailer, N., & Weinmann, A. (2022). Digital transformation in business and management research: An overview of the current status quo. *International Journal of Information Management*, 63, 102466. doi:10.1016/j.ijinfomgt.2021.102466
- Laïfi, A., & Jossierand, E. (2016). Legitimation in practice: A new digital publishing business model. *Journal of Business Research*, 69(7), 2343–2352. doi:10.1016/j.jbusres.2015.10.003
- Li, S., Gao, L., Han, C., Gupta, B., Alhalabi, W., & Almakdi, S. (2023). Exploring the effect of digital transformation on Firms' innovation performance. *Journal of Innovation & Knowledge*, 8(1), 100317. doi:10.1016/j.jik.2023.100317
- Lim, C. Y., Wang, J., & Zeng, C. (2018). China's "Mercantilist" Government Subsidies, the Cost of Debt and Firm Performance. *Journal of Banking & Finance*, 86, 37–52. doi:10.1016/j.jbankfin.2017.09.004
- Lim, S., & Zhu, J. (2016). A note on two-stage network DEA model: Frontier projection and duality. *European Journal of Operational Research*, 248(1), 342–346. doi:10.1016/j.ejor.2015.06.050
- Liu, B., Wang, J., Li, R. Y. M., Peng, L., & Mi, L. (2022). Achieving carbon neutrality—the role of heterogeneous environmental regulations on urban green innovation. *Frontiers in Ecology and Evolution*, 10, 923354. doi:10.3389/fevo.2022.923354
- Liu, B., Zheng, K., Zhu, M., Wu, F., & Zhao, X. (2023). Towards sustainability: The impact of industrial synergistic agglomeration on the efficiency of regional green development. *Environmental Science and Pollution Research International*, 1–13. doi:10.1007/s11356-023-28449-1 PMID:37391560
- Liu, X., Li, H., Sun, Y., & Wang, C. A. (2022). High-speed railway and urban productivity disparities. *Growth and Change*, 53(2), 680–701. doi:10.1111/grow.12602
- Long, X., & Pelloni, A. (2017). Factor income taxation in a horizontal innovation model. *Journal of Public Economics*, 154, 137–159. doi:10.1016/j.jpubeco.2017.06.008
- Mann, G., Karanasios, S., & Breidbach, C. F. (2022). Orchestrating the digital transformation of a business ecosystem. *The Journal of Strategic Information Systems*, 31(3), 101733. doi:10.1016/j.jsis.2022.101733
- Marcon, É., Le Dain, M.-A., & Frank, A. G. (2022). Designing business models for Industry 4.0 technologies provision: Changes in business dimensions through digital transformation. *Technological Forecasting and Social Change*, 185, 122078. doi:10.1016/j.techfore.2022.122078
- Miric, M., Boudreau, K. J., & Jeppesen, L. B. (2019). Protecting their digital assets: The use of formal & informal appropriability strategies by App developers. *Research Policy*, 48(8), 103738. doi:10.1016/j.respol.2019.01.012
- Mithani, M. A. (2023). Scaling digital and non-digital business models in foreign markets: The case of financial advice industry in the United States. *Journal of World Business*, 58(4), 101457. doi:10.1016/j.jwb.2023.101457
- Möller, K., Nenonen, S., & Storbacka, K. (2020). Networks, ecosystems, fields, market systems? Making sense of the business environment. *Industrial Marketing Management*, 90, 380–399. doi:10.1016/j.indmarman.2020.07.013
- Moshirian, F., Tian, X., Zhang, B., & Zhang, W. (2021). Stock market liberalization and innovation. *Journal of Financial Economics*, 139(3), 985–1014. doi:10.1016/j.jfineco.2020.08.018
- Mota, J., Santos, J. N., & Alencar, R. (2023). Intertwining innovation and business networks for sustainable agricultural systems: A case study of carbon-neutral beef. *Technological Forecasting and Social Change*, 190, 122429. doi:10.1016/j.techfore.2023.122429
- Namasudra, S., & Roy, P. (2018). PpBAC: Popularity Based Access Control Model for Cloud Computing. [JOEUC]. *Journal of Organizational and End User Computing*, 30(4), 14–31. doi:10.4018/JOEUC.2018100102
- Nathan, M., & Rosso, A. (2015). Mapping digital businesses with big data: Some early findings from the UK. *Research Policy*, 44(9), 1714–1733. doi:10.1016/j.respol.2015.01.008
- Neumann, N., Tucker, C. E., & Whitfield, T. (2019). Frontiers: How Effective Is Third-Party Consumer Profiling? Evidence from Field Studies. *Marketing Science*, 38(6), 918–926. doi: doi:10.1287/mksc.2019.1188
- Ozen, O., & Ozturk-Kose, E. (2023). Management innovation: The role of internal, external factors, and business group affiliation. *Journal of Business Research*, 164, 113964. doi:10.1016/j.jbusres.2023.113964

- Pasinetti, L. L. (2021). Economic theory and institutions. *Structural Change and Economic Dynamics*, 56, 438–442. doi:10.1016/j.strueco.2019.12.005
- Prajogo, D. I. (2016). The strategic fit between innovation strategies and business environment in delivering business performance. *International Journal of Production Economics*, 171, 241–249. doi:10.1016/j.ijpe.2015.07.037
- Qiang, C. Z., Wang, H., & Xu, L. C. (2021). Ownership, Enforcement, and the Effects of Business Environment. *Journal of Government and Economics*, 2, 100007. doi:10.1016/j.jge.2021.100007
- Reyes, J.-D., Roberts, M., & Xu, L. C. (2021). The heterogeneous growth effects of the business environment: Firm-level evidence for a global sample of cities. *China Economic Quarterly International*, 1(1), 15–28. doi:10.1016/j.ceqi.2020.09.001
- Ribeiro, B., & Shapira, P. (2020). Private and public values of innovation: A patent analysis of synthetic biology. *Research Policy*, 49(1), 103875. doi:10.1016/j.respol.2019.103875 PMID:32015589
- Rosado-Cubero, A., Hernández, A., Blanco Jiménez, F. J., & Freire-Rubio, T. (2023). Promotion of entrepreneurship through business incubators: Regional analysis in Spain. *Technological Forecasting and Social Change*, 190, 122419. doi:10.1016/j.techfore.2023.122419
- Scherrer, S., & Perrig, A. (2021). Security, Anonymity, Privacy, and Trust. In M. Toy (Ed.), *Future Networks, Services and Management: Underlay and Overlay, Edge, Applications, Slicing, Cloud, Space, AI/ML, and Quantum Computing* (pp. 367–381). Springer International Publishing. doi:10.1007/978-3-030-81961-3\_13
- Shin, D., & Park, Y. J. (2019). Role of fairness, accountability, and transparency in algorithmic affordance. *Computers in Human Behavior*, 98, 277–284. doi:10.1016/j.chb.2019.04.019
- Şimşek, T., Öner, M. A., Kunday, Ö., & Olcay, G. A. (2022). A journey towards a digital platform business model: A case study in a global tech-company. *Technological Forecasting and Social Change*, 175, 121372. doi:10.1016/j.techfore.2021.121372
- Struckell, E., Ojha, D., Patel, P. C., & Dhir, A. (2022). Strategic choice in times of stagnant growth and uncertainty: An institutional theory and organizational change perspective. *Technological Forecasting and Social Change*, 182, 121839. doi:10.1016/j.techfore.2022.121839
- Teece, D. J. (2018). Profiting from innovation in the digital economy: Enabling technologies, standards, and licensing models in the wireless world. *Research Policy*, 47(8), 1367–1387. doi:10.1016/j.respol.2017.01.015
- Varadarajan, R. (2020). Customer information resources advantage, marketing strategy and business performance: A market resources based view. *Industrial Marketing Management*, 89, 89–97. doi:10.1016/j.indmarman.2020.03.003
- Varriale, V., Cammarano, A., Michelino, F., & Caputo, M. (2021). The role of supplier innovation performance and strategies on the smartphone supply market. *European Management Journal*. doi:10.1016/j.emj.2021.09.010
- Vo, X. V., Nguyen, T. L. A., Tuan, L. Q., Luu, H. N., & Vu, K. T. (2020). Local business environment, domestic CEOs and firm performance in a transitional economy: Empirical evidence from Vietnam. *Economic Analysis and Policy*, 66, 236–249. doi:10.1016/j.eap.2020.04.006
- Wang, C. A., Liu, X., Li, H., & Yang, C. (2023). Analyzing the impact of low-carbon city pilot policy on enterprises' labor demand: Evidence from China. *Energy Economics*, 124(8), 106676. doi:10.1016/j.eneco.2023.106676
- Wang, C. A., Wu, J., & Liu, X. (2022). High-speed rail and urban innovation: Based on the perspective of labor mobility. *Journal of the Asia Pacific Economy*, 1–26. doi:10.1080/13547860.2022.2058257
- Wang, C. A., Wu, J., Ruan, J., & Liu, X. (2022). Language differences, cultural identity, and innovation. *Growth and Change*, 53(4), 1716–1736. doi:10.1111/grow.12631
- Wang, R., Xue, Y., & Zheng, W. (2021). Does high external debt predict lower economic growth? Role of sovereign spreads and institutional quality. *Economic Modelling*, 103, 105591. doi:10.1016/j.econmod.2021.105591

- Wang, X., Zou, H., Zheng, Y., & Jiang, Z. (2019). How will different types of industry policies and their mixes affect the innovation performance of wind power enterprises? Based on dual perspectives of regional innovation environment and enterprise ownership. *Journal of Environmental Management*, 251, 109586. doi:10.1016/j.jenvman.2019.109586 PMID:31563050
- Wani, A. S. R., & Khaliq, R. (2021). SDN-based intrusion detection system for IoT using deep learning classifier (IDSIoT-SDL). *CAAI Transactions on Intelligence Technology*, 6(3), 281–290. doi:10.1049/cit.2.12003
- Wiredu, G. O., Boateng, K. A., & Effah, J. K. (2021). The platform executive: Technology shaping of executive cognition during digital service innovation. *Information & Management*, 58(4), 103469. doi:10.1016/j.im.2021.103469
- Wong, W. P., Sinnandavar, C. M., & Soh, K.-L. (2021). The relationship between supply environment, supply chain integration and operational performance: The role of business process in curbing opportunistic behaviour. *International Journal of Production Economics*, 232, 107966. doi:10.1016/j.ijpe.2020.107966
- Yang, M., & Han, C. (2021). Stimulating innovation: Managing peer interaction for idea generation on digital innovation platforms. *Journal of Business Research*, 125, 456–465. doi:10.1016/j.jbusres.2019.08.005
- Yang, Y., Jia, F., Chen, L., Wang, Y., & Xiong, Y. (2021). Adoption timing of OHSAS 18001 and firm performance: An institutional theory perspective. *International Journal of Production Economics*, 231, 107870. doi:10.1016/j.ijpe.2020.107870
- Yu, F., Du, H., Li, X., & Cao, J. (2023). Enterprise digitalization, business strategy and subsidy allocation: Evidence of the signaling effect. *Technological Forecasting and Social Change*, 190, 122472. doi:10.1016/j.techfore.2023.122472
- Yu, L., Tang, X., & Huang, X. (2023). Does the business environment promote entrepreneurship?—Evidence from the China Household Finance Survey. *China Economic Review*, 79, 101977. doi:10.1016/j.chieco.2023.101977
- Zafari, K., Biggemann, S., & Garry, T. (2023). Development of business-to-business relationships in turbulent environments. *Industrial Marketing Management*, 111, 1–18. doi:10.1016/j.indmarman.2023.03.002
- Zhang, H., Liu, Q., & Wei, Y. (2023). Digital product imports and export product quality: Firm-level evidence from China. *China Economic Review*, 79, 101981. doi:10.1016/j.chieco.2023.101981
- Zhang, J., & Guan, J. (2018). The time-varying impacts of government incentives on innovation. *Technological Forecasting and Social Change*, 135, 132–144. doi:10.1016/j.techfore.2018.04.012
- Zhang, X., He, P., Liu, X., & Lu, T. (2023). The effect of low-carbon transportation pilot policy on carbon performance: Evidence from China. *Environmental Science and Pollution Research International*, 30(19), 1–29. doi:10.1007/s11356-023-25940-7 PMID:36879091
- Zhang, Y., Ma, X., Pang, J., Xing, H., & Wang, J. (2023). The impact of digital transformation of manufacturing on corporate performance—The mediating effect of business model innovation and the moderating effect of innovation capability. *Research in International Business and Finance*, 64, 101890. doi:10.1016/j.ribaf.2023.101890
- Zhao, X., Yi, C., Zhan, Y., & Guo, M. (2022). Business environment distance and innovation performance of EMNEs: The mediating effect of R&D internationalization. *Journal of Innovation & Knowledge*, 7(4), 100241. doi:10.1016/j.jik.2022.100241



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