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Research on the nonlinear effects of technological progress on output of manufacturing firms

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ABSTRACT

This study constructs a theoretical framework for technological progress (TP) on firm output (FOP) and examines the nonlinear influence between them. First, the empirical findings indicate that TP has a “positive U-shaped” correlation with FOP. This impact is particularly pronounced among firms characterized by high technological intensity, older age, location in eastern regions, and presence in high-innovation-policy environments. Second, the TP of enterprises further affects the output of enterprises by affecting their operating expenses, labor costs, and production capacity. Most importantly, this study shows that quality competitiveness plays a significant role in moderating the interaction between TP and FOP. Specifically, in the early stages of TP, the addition of industry quality competitiveness amplifies the inhibitory effect of TP on FOP. However, when TP further develops, quality competitiveness enhances the promotional effect of TP on FOP. In the initial phase of technological advancements, quality competitiveness mitigates the negative influence that TP may exert on FOP. This study contributes to the existing body of knowledge, offering Chinese insights to complement existing research and holding both scholarly and practical relevance for the progression of other emerging economies.

Introduction

With the in-depth development of industrialization, the driving force of economic growth has gradually shifted from high-density labor input, resource consumption, air pollution, and high capital input to technological progress (TP) and quality improvement. At this stage, the sustainable development of manufacturing enterprises can promote the optimization of industrial structure and lay a robust groundwork for economic transformation and progress while strengthening and elevating the country’s position and impact within the global economic system. Developed countries have successively introduced the “Industry 4.0″ strategy, aiming to revitalize the manufacturing sector through technological innovation, industrial upgrading, and “re-industrialization” policies to boost economic development (Shi et al., 2023). As a leading emerging economy, China has highlighted the importance of accelerating the development of a manufacturing powerhouse, emphasizing that China’s manufacturing sector continues to play a crucial role in supporting, driving, and securing the nation at its current stage. China is accelerating the transformation from “Made in China” to a new development model of “Created in China” (Zeng et al., 2024). However, faced with increasing uncertainties in the international economic environment, the significant rise in global inflationary pressure, the high cost of raw materials, and other problems, the development space of Chinese manufacturing enterprises is constantly shrinking (Chen et al., 2024).

Given the economic background of exploring how to break through the development dilemma and promote the healthy economic development of manufacturing enterprises to enhance the driving force of economic development, academia has generally recognized the importance of TP (Faruq, 2010; Tian, 2024; Xu & Liu, 2024). Previous studies have fully analyzed the impact of technological advancement on the growth of manufacturing enterprises (Fazlıoğlu et al., 2019; Giancarlo et al., 2022; Nie et al., 2024), establishing the important role of TP. However, current research has not fully elucidated the specific relationship between TP and enterprise development (Lautier, 2024). Additionally, existing studies lack an in-depth discussion on the influencing mechanism between TP and the output of manufacturing firms. With this objective, this study seeks to address the following research questions.

RQ1: How does a firm’s technological progress influence its firm output? Is the effect positive or negative? Is it linear or nonlinear?

RQ2: What is the mechanism path between technological progress and firm output? What variables play mediating and moderating roles?

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To address these questions, this study conducted an in-depth analysis of the role, impact, and mechanisms through which TP influences enterprise growth. The primary contributions of this research are summarized as follows. (1) This research introduces the endogenous growth theory and nonlinear panel model to verify the nonlinear impact of TP on firm output (FOP) using both theoretical and empirical approaches, which enriches the existing theoretical research framework. (2) The intermediary mechanism between TP and enterprise output is expounded, providing a theoretical basis for firms to conduct TP activities. (3) This study utilizes data from Chinese industrial enterprises and A-share listings to provide the Chinese experience for the healthy development of manufacturing enterprises in other emerging markets to promote the healthy development of other emerging economies.

The rest of this study is structured as follows: Part 2 reviews the relevant literature. Part 3 outlines the theoretical framework and proposes the research hypotheses. Part 4 describes the model specification and variable selection. Part 5 reports the empirical findings and discusses the results. Part 6 conducts additional analyses. Finally, provides the conclusion and outlook.

Literature review

Related research on technological progress and firm output

The TP has been extensively studied as a key driving force affecting the development of manufacturing enterprises and the economy. Scholars have adopted various quantitative evaluation methods to measure TP, including the number of patents granted, patent applications, new technology introduction activities, internal R&D expenditures, and total factor productivity. (Tan et al., 2014; Mariev et al., 2022; David & Presley, 2023; Xu & Liu, 2024).

TP and its impact on the output of manufacturing firms have been prominent topics in academic research. Regarding studies focusing on developed countries, Yang et al. (2021) explored the link between TP and manufacturing sector growth based on the manufacturing data of the United States. The results showed that firms' capital input can promote TP, which can realize the substitution of labor skills and improve production efficiency and manufacturing development. Studley (2021) concentrated on the growth of manufacturing firms in the US, and his research results further confirmed that it was effective for manufacturing enterprises to adopt TP as a strategy to alleviate cost pressure. This finding provides a strategy for manufacturing firms to respond to market changes and provides a new perspective on the role of TP in advancing manufacturing firms.

In terms of emerging market research, Yueh (2009) evaluated the impact of intellectual property protection in China. The empirical results showed that the number of patents positively correlated with foreign direct investment and innovation activities under R&D policies. Therefore, adopting new technologies can enhance industrial production efficiency and support sustainable economic growth. Fazlıoğlu et al. (2019) used Turkish manufacturing data to study the impact of technological innovation on manufacturing firm growth. These findings indicate that any form of technological innovation can greatly enhance the total factor productivity (TFP) of manufacturing firms. Khanna and Sharma (2021) used data from 900 manufacturing companies in India from 2000 to 2016 to examine the link between TP input and the output efficiency of manufacturing enterprises and found that enterprises with higher technological input tend to obtain higher production efficiency.

Related research on quality competitiveness and firm development

Quality is a key factor in the development of companies, industries, and national economies (Liu et al., 2024). To maximize their own development interests, enterprises focus on market supply and demand dynamics and enhance their own and the industry's quality competitiveness index (QCI). Currently, for Chinese manufacturing enterprises, QCI is the key to enhancing market share and achieving structural reverse reform (Brambilla & Porto, 2016). The majority of existing studies construct a QCI analytical framework grounded in the development performance of manufacturing firms (Jürgen et al., 2022).

In terms of developed market research, Leachman et al. (2005) measured the QCI of the US automobile manufacturing industry from four aspects—R&D investment, production process time compression, and outsourcing degree—to evaluate the manufacturing competitiveness of enterprises against their main competitors. All these factors were found to affect the QCI of the manufacturing industry and further influence its performance. Faruq (2010) used US export data to prove the link between product quality and industrial exports. Using export data from Central and Eastern European countries, Bierut and Pawlak (2017) studied the factors affecting exports and found that improvements in institutional and regulatory quality stimulate export growth.

In terms of emerging market research, Benkovskis and Wörz (2015) developed export price indices and assessed the manufactured exports of six ASEAN members, as well as China, Japan, and South Korea. The results show that between 2000 and 2011, the export products of the aforementioned countries were significantly associated with the quality factor of the non-price factor. Wang (2023) used the differences-in-differences method to research the factors affecting the growth of China's manufacturing exports. The study showed that the constraints of environmental protection policies and enhanced innovation capabilities drive changes in the competitiveness of enterprise structure and product quality, thereby promoting an increase in China's export volume.

Nonlinear impact of firm output

Some scholars have begun to focus on nonlinear impacts in the manufacturing industry. Most studies focused on the development experiences of manufacturing enterprises in emerging markets. Anusha and Laura (2014) studied the impact of India's marketization process on manufacturing enterprises. These findings indicate a notable nonlinear relationship between the distributional effects of deregulation on firm size. Specifically, after further deregulation, the degree of resource allocation distortion decreases, and the likelihood of SMEs entering the market increases. Wang et al. (2023) used data from China's manufacturing sector, selecting 757 A-share-listed manufacturing firms from 1995 to 2019, to examine the link between open innovation and innovation performance. They discovered an "inverted U-shaped" relationship between open innovation and performance, where moderate innovation enhances enterprise performance, but excessive innovation hinders it. Nie et al. (2024) utilized data from China's manufacturing sector to empirically examine the effects of green innovation on high-quality development and found an inverted U-shaped relationship between green research intensity and social performance.

In terms of research on developed countries, Leachman et al. (2005) studied seven automobile manufacturers in the US, Japan, and Germany to analyze the nonlinear impact of R&D on the development of these companies. These findings suggest that both a firm's R&D activities and outsourcing may lead to a further decline in performance. Cardamone (2012) analyzed data from 1230 Italian manufacturing firms in 2003 to examine how R&D influences production within a nonlinear production function framework. Polemis and Stengos (2015) used US manufacturing data to explore the effects of market structure on competition and wages, revealing a nonlinear link between market competition and labor productivity.

Literature gaps

Organizing the existing research, the relevant research on TP and enterprise development was found to be relatively rich; however, many deficiencies remain, which are summarized as follows:

(1) Inappropriate indicator selection can result in biased estimation. Most existing studies assess enterprise TP based on TFP. However, the measurement method of TFP is unique, as it represents not only the technical progress of enterprises but also the improvement of the overall efficiency of manufacturing enterprises, such as capital utilization efficiency and labor output capacity. The rise in overall efficiency will inevitably enhance the added value of manufacturing firms, which results in a deviation from existing research results on TP and enterprise development.
(2) Few studies have focused on the nonlinearity of TP and enterprise development, and the sample size of the research is small, leading to a lack of persuasive results. Upon reviewing the existing research, some scholars have evidently begun focusing on factors influencing the nonlinear development of the manufacturing industry, such as open innovation and environmental regulation. However, few researchers have explored the nonlinear impact of TP on enterprise development. Among them, research on relevant nonlinear effects mainly selects a few manufacturing enterprises and industrial data as sample data, and the empirical results are random and not persuasive.
(3) The moderating effect of the QCI has not yet been thoroughly explored. Existing studies on the QCI primarily focus on its direct impact on firms, such as enhancing export competitiveness and promoting market share expansion (Leachman et al., 2005; Faruq, 2010). However, few studies have examined the potential of the QCI as a moderating variable in complex economic activities, particularly regarding its dynamic influence on the relationship between firm performance and output.

To address these issues, this study analyzed extensive survey data from Chinese industrial enterprises, using the number of invention patents granted as a proxy for measuring TP. A nonlinear panel regression model was utilized to examine the nonlinear impact of TP on enterprise development. Additionally, this research explored the overall role of the QCI as a moderating variable and empirically verified its differential effects during the initial and subsequent stages of TP development.

Theoretical process and research hypotheses

Nonlinear effect of technological progress on firm output

To further investigate the relationship between TP and FOP, this study introduced endogenous growth theory as the theoretical framework for analysis. Endogenous growth theory clearly indicates that the fundamental driving force of economic growth arises from factors within enterprises, especially TP, which plays a pivotal role. In this theoretical framework, TP is regarded as an endogenous variable, meaning that its generation and development are determined by decisions and actions within the manufacturing industry rather than simply influenced by external forces. This research perspective is helpful for more accurately understanding the complex relationship between TP and manufacturing enterprises.

Technological progress

Firm's TP is determined by research and development investment (R&D) and human capital (H), and is an increasing function of the two. This reflects the endogeneity of TP, meaning that it is driven by resource allocation and human capital accumulation within the firm. This can be expressed as:

$$T = f(RD, H) \tag{1}$$

satisfying $\frac{dT}{\partial f(RD)} > 0$, $\frac{dT}{\partial f(H)} > 0$. In Eq. (1), T represents TP, RD denotes enterprise R&D expenditure, and H refers to human capital. According to Araújo et al. (2023), internal R&D expenditure plays a crucial role in promoting TP within the manufacturing industry.

To simplify the model, we assume a linear relationship between TP, R&D, and human capital, as shown in Eq. (2):

$$A = \beta_1 \times RD + \beta_2 \times H \tag{2}$$

In Eq. (2), both A and B are greater than zero, and the other variables are defined in the same manner as in Eq. (1).

Quality competitiveness

TP enhances the QCI of the industry by improving product quality and innovation capability, while market demand affects the QCI through consumer preferences and market competition. Therefore, the industry QCI is assumed to be affected by internal TP (A) and market demand, as shown in Eq. (3):

$$QCI_j = q\left(f_j(T_i), D\right) \tag{3}$$

Where $i = 1, 2, \ldots, n$, satisfying $\frac{dQCI_j}{\partial q\left(f_j(T_i)\right)} > 0$, $\frac{dQCI_j}{qf(D)} > 0$. In Eq. (3), QCI_j represents the quality competitiveness level of industry j; $f_j(T_i)$ denotes the technological level of industry j; $f_j(T_i)$ is an increasing function of the TP level of enterprises; and n is the number of firms in industry j. The QCI of the industry is crucial for meeting consumer demand for quantity while also catering to preferences for quality following further industrialization. Eq. (3) shows that QCI is an increasing function of TP within the manufacturing industry. To further simplify the model, we assume a linear relationship between industry QCI, TP, and market demand:

$$QCI_j = \omega_1 \times f_j(T_i) + \omega_2 \times D_j \tag{4}$$

In Eq. (4), T_i is the endogenous variable of enterprise i, and D_j is the market demand of industry j. Historically, market demand is an exogenous variable that generally remains stable. Eq. (4) suggests that QCI_j is an intermediate variable determined by the joint effect of the endogenous variable T_i and the exogenous variable D_j.

Firm output function

The endogenous growth model theory emphasizes that enterprise output is a dynamic process and that promoting TP is key to the sustainable development of enterprises. Therefore, an enterprise output model should consider the long-term effects of these factors and their influence on enterprise development over time. Following Roufagalas and Orlov (2020), we set the endogenous economic growth model as follows:

$$Y = A(T) \times QCI \times K^{\alpha} \times L^{1-\alpha} - C(T) \tag{5}$$

In Eq. (5), α is the capital-output elasticity, $\alpha \in (0,1)$, and $1-\alpha$ is the labor input-output elasticity. Generally, $K^{\alpha} \times L^{1-\alpha}$ is an identifiable constant. In Eq. (5), $A(T)$ is the technological development level of the enterprise, which can represent the technological intensity of the enterprise and is positively correlated with TP. $C(T)$ is the enterprise's production cost, which is also positively correlated with TP. The above equation shows a possible nonlinear "positive U-shaped" association between TP and FOP. Specifically, when the TP level of enterprises is low, although TP can improve production efficiency, it has little impact on enterprise output. Additionally, because of the need to develop new technologies, enterprises must invest significant funds in R&D and equipment purchases, leading to a further increase in production cost, C (T). That is, enterprises in the early stage of TP are prone to the phenomenon where $A(T) \times QCI \times K^{\alpha} \times L^{1-\alpha} < C(T)$. At this stage, the behavior of TP has a negative impact on FOP. However, with the further deepening of TP (T), the increase in marginal benefit brought by new technology gradually exceeds the increase in marginal cost, and the phenomenon of $A(T) \times QCI \times K^{\alpha} \times L^{1-\alpha} > C(T)$ exists in the enterprise at this time. This development results in a "positive U-shaped" association between TP and FOP. Building on this analysis, this study formulates Hypothesis 1.

H1. TP and FOP are related in a "positive U-shaped" manner.

Given the variations in enterprise conditions and their respective regions, the above hypothesis may exhibit obvious heterogeneity. Eq. (5) shows that the heterogeneity of many factors, such as enterprise technology intensity and enterprise labor input, may lead to large heterogeneity in enterprise output. The production efficiency of enterprises with different technological intensities may be fundamentally different (Hu et al., 2024). Considering the significant differences in the initial factors across enterprises, such as some having advanced technological development and others having a lower level, this leads to fundamental heterogeneity in the TP and output of firms with varying technological capabilities. As an important endogenous variable, enterprise age may have significant effects on enterprise development. Older enterprises that have been deeply engaged in a certain field for many years are better able to grasp the development direction of the field (Chen & Wang, 2024). Significant differences exist within regions in China, with significant heterogeneity in policies, resources, and the degree of market development among different regions. Consequently, strong consistency exists in enterprise production within the region, while large heterogeneity exists among different regions (Hou et al., 2020). Therefore, different regions may lead to a relatively typical heterogeneity gap between TP and enterprise production. Based on above theoretical analysis, this study formulates Hypothesis 2:

H2. The positive U-shaped relationship between TP and FOP varies across enterprises of different technological intensities, ages, and regions.

Mediating effect between technological progress and firm output

According to the Cobb-Douglas production function theory, FOP factors depend on capital, labor, and technological efficiency (Khanna & Sharma, 2024). In the initial stage of TP, firms must typically invest significant upfront costs to introduce new technologies. This includes expenses for purchasing advanced production equipment, direct R&D costs for new technologies, and infrastructure costs for modifying production lines and expanding factories to accommodate new technologies. These substantial expenditures lead to a sharp increase in business costs. At this stage, since the new investments have not yet translated into actual output benefits, the firm's output not only fails to grow significantly but may also be suppressed due to the increased cost burden. However, according to the innovation diffusion theory, the introduction and application of technology permeate various aspects of the firm and require time (Wang et al., 2025). As new technologies mature and production processes are optimized, firms begin to enjoy the dividends of economies of scale. New technologies improve production accuracy and stability, reduce scrap rates, and minimize raw material waste, thereby lowering the unit product's raw material costs. Conversely, efficient management systems generated by TP help optimize supply chain processes and reduce logistics costs, warehousing costs, and other operating expenses. At this point, the continuous reduction in operating costs becomes a driving force for significant growth in FOP, presenting a positive U-shaped trajectory consistent with the company's TP. According to the resource-based view (Barney, 1991), the operating expenses that firms invest in improving their technological capabilities influence their core competitiveness and, in turn, affect development performance. While TP may lead to higher operating costs in the short term, potentially squeezing profits, it builds a competitive advantage through technological accumulation, resulting in positive effects on long-term firm development. Furthermore, Bloom et al. (2012) verified through global company data that, after technology matures, the reduction in operating costs is significantly positively correlated with improved productivity, directly contributing to revenue growth.

In terms of TP, labor costs, and FOP, the impact of TP on employee costs also reflects the contradiction between short- and long-term benefits. TP encourages firms to transition to knowledge- and skill-intensive models. According to human capital theory, a firm's technological efficiency must align with a highly skilled workforce to maximize technological efficiency (Acemoglu & Restrepo, 2020). To meet the requirements of new technologies, firms must invest substantial funds in training employees to enhance their professional skills, enabling them to proficiently operate new equipment and utilize new technologies. Firms may face two types of high employee costs during this process. One is the increased expenditure on recruiting highly skilled talent. The other is additional investment in training existing employees to adapt to new technologies. It is important to note that technological progress increases the demand for high-skilled labor, raising labor costs in the short run. However, in the long run, the complementarity between skills enhances output efficiency, which in turn reduces unit costs (Acemoglu, 2002). Hellerstein et al. (1999) confirmed that firm investments in human capital, such as employee training costs, are significantly positively correlated with firm output. Moreover, the higher the proportion of skilled workers, the stronger the firm's output growth. Additionally, high labor costs compel firms to further optimize management processes and technology applications, ultimately boosting output and creating a "cost pressure-efficiency improvement-output growth" chain (Bloom et al., 2012).

TP's impact on improving a firm's production capacity is one of the core pathways influencing output. In the early stages of TP, firms face challenges in connecting new and old technologies, which may lead to compatibility issues between new equipment and existing production processes, resulting in production stagnation and delays, and even a decline in production efficiency. Firms' absorption of new technology follows a "J-shaped curve," with a decline in efficiency during the adaptation phase, followed by a productivity surge as the technology matures, significantly boosting output (Comin & Hobijn, 2010). Additionally, the initial application of new technologies often involves extensive debugging work, consuming a significant amount of production time and making it difficult for firms to achieve rapid output growth in the short term. However, as new technologies become more refined, firms adopt more advanced production processes to improve production line efficiency and reliability. Technological innovation introduces new products, processes, and organizational methods, promoting the expansion of production capacity. Improvement in production capacity is primarily reflected in faster production speeds and expanded production scales. The application of new technologies is often accompanied by higher levels of automation and digitalization, which not only reduces redundant steps in the production process but also enhances resource utilization efficiency. Simultaneously, based on the economies of scale theory, when firms achieve technological upgrades, they can more effectively utilize existing resources and expand production capacity, thus improving market competitiveness and economic efficiency (Romer, 1990). The Neoclassical Growth Theory proposed by Solow (1957) suggests that improvements in production efficiency are core drivers of long-term economic growth. At the firm level, increased production efficiency directly expands the output frontier, creating economies of scale and promoting output growth. Based on these insights, Hypothesis 3 was proposed.

H3a. Operating expenses mediate the nonlinear relationship between TP and FOP.

H3b. Labor costs mediate the nonlinear effect of TP and FOP.

H3c. Production capacity mediates the nonlinear relationship between TP and FOP.

Moderating role of quality competitiveness

Schumpeter's theory of innovation emphasizes that TP is the core driving force behind firm development, with the QCI facilitating the internalization of TP (Park et al., 2023). Firms' TP encompasses not only technological innovation but also product, market, and organizational innovation, among other aspects. This theory posits that firms can break the existing market equilibrium and achieve excess profits by introducing new production technologies or methods, thereby incentivizing more firms to engage in innovative activities and promote economic development and structural change. In this process, the QCI is closely linked to firms' TP. In the early stages of TP, to meet the higher quality standards for the QCI, firms must invest more resources in TP, which suppresses their initial benefits. At this point, the introduction of innovation involves a trade-off between costs and benefits. However, in the later stages of TP, firms with a strong QCI can better leverage the effects of TP. They enhance technological standards and optimize production processes, effectively absorbing the high costs of TP and improving production efficiency and product quality. This helps firms gain bargaining power based on quality, capture a larger market share, and ultimately achieve an overall increase in output. This reflects the nonlinear impact of TP on FOP under the influence of the QCI. Fig. 1 summarizes the theoretical process and research hypotheses of this study.

H4. The QCI plays a moderating effect on the nonlinear impact of TP on FOP.

Study design

Data sources

This study examined the TP and output of Chinese manufacturing firms. To ensure the credibility of the findings, we used data from Chinese industrial enterprises between 2005 and 2014 in the benchmark regression. This is a firm-level survey database with the largest sample size and widest coverage in China. To minimize sample selection bias and address potential regression result distortions from outdated data, this study incorporated data from China's A-share listed companies (2007–2023) into a robustness analysis for further testing. In terms of data preprocessing, we applied the data processing method used by Brandt et al. (2012): (1) eliminate the samples of enterprises with fewer than eight employees; (2) exclude enterprises with operating costs less than zero; (3) eliminate the samples with more missing values of major indicators, such as the number of employees and total amount of fixed assets; and (4) match the manufacturing firm data with the Chinese patent database. Finally, a total of 958,059 pieces of data on Chinese industrial enterprises and 19,726 pieces of A-share listing data points from 2005 to 2023 were obtained. This study aligns industry quality competitiveness with the "National Manufacturing Quality Competitiveness Index Bulletin" issued by the General Administration of Quality Supervision, Inspection, and Quarantine for subsequent empirical research.

Variable selection

Dependent variable: firm output (FOP)

Firm output refers to the economic results obtained by the enterprise through the input of production materials and use of internal production resources within a certain period. Compared with operating income, total profit, and other indicators, industrial added value has the advantages of fully reflecting production activities, ease of quantification and comparison, and the exclusion of non-productive activities. Since industrial added value is the most reasonable and effective measure of enterprise output, this study used it as the proxy for FOP, following Lin et al. (2024). To ensure consistency in units, this study applied a logarithmic transformation to the variables mentioned above.

Independent variable: technological progress (TP)

The number of invention patent authorizations obtained by enterprises represents the determination and willingness of economic entities to conduct TP activities. Unlike utility models and design patents, invention patents demand greater technological investment and longer R&D processes. Therefore, the number of invention patents granted reflects enterprises' R&D investments in their TP. In summary, the number of invention patents awarded to enterprises is the most accurate indicator of their TP. Therefore, following Xie et al. (2024), this research used the number of invention patents granted as a measure of TP. To avoid multicollinearity, we log-transformed the number of patents. Furthermore, considering the theoretical analysis indicating a nonlinear impact of TP on FOP, the quadratic term of TP was introduced as an independent variable.

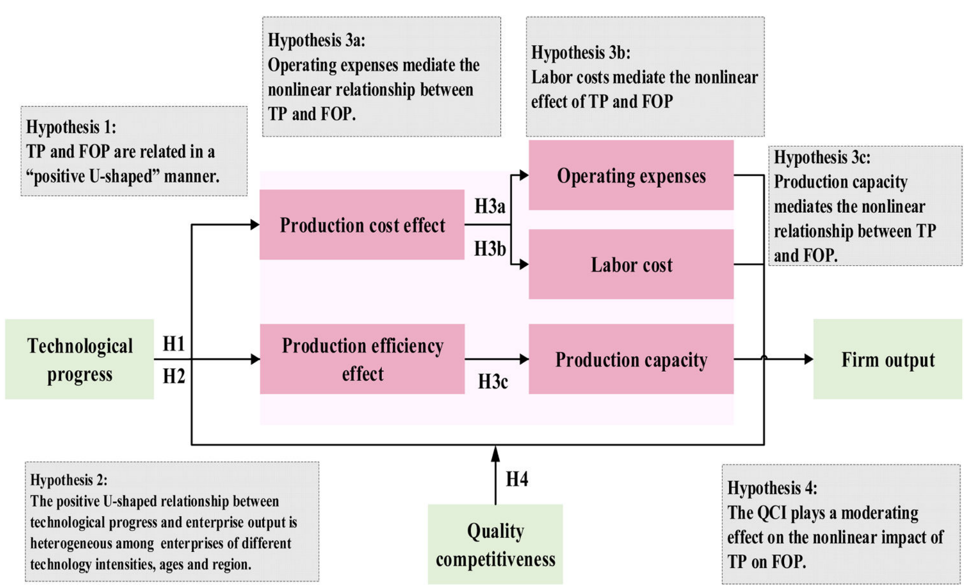

Fig. 1. The influence mechanism diagram.

Control variables

To enhance results accuracy and reliability, industry scale, labor cost growth rate, and total asset value of manufacturing enterprises were included as control variables. The details are as follows:

Ratio of fixed assets to employees (RFAE): Generally, fixed capital is regarded as the basic R&D input of enterprises and has a significant impact on enterprise production. To remove the effect of capital input on industrial added value and better highlight the role of TP in improving manufacturing efficiency, this study drew on Martino (2015) and Juelsrud and Wold (2020) and used the ratio of fixed capital to employees as a measure of fixed assets and workforce size.

Industry scale (INDS): An industry's size often directly influences its added value. A larger industry scale may result in higher production efficiency, wider market coverage, and stronger resource integration ability, all of which may improve industrial added value. However, this improvement may not be entirely attributable to TP. Therefore, referring to Huang (2022), this study used the logarithm of total employees as a proxy for industry scale. To standardize these dimensions, we applied a logarithmic transformation to firm size.

Total assets (TTA): There may be considerable variations in total assets across industries or enterprises within the manufacturing sector. Therefore, following Khan et al. (2017), we selected the total assets of each industry as a control variable. To avoid multicollinearity, this study logarithmizes the total assets for each enterprise.

Total profits (TTP): There may be notable variations in profitability levels among enterprises, which are reflected in the large gap in profit rates between enterprises. If the total profit of enterprises is not controlled, changes in FOP are likely to be caused by differences in industry profitability rather than TP. Therefore, we followed Camila et al. (2023) and selected the total profit of each firm as a control variable. To standardize the dimensions, we applied a logarithmic transformation to the total profits.

Enterprise age (AGE): The enterprise's age usually represents its maturity and experience. However, a firm's age affects its market share, management experience, ability to acquire resources, and technological advancement. To mitigate the influence of enterprise age on the results, this study followed Jiang et al. (2023) and used enterprise age as a control variable.

Asset-liability ratio (ALR): An enterprise's financial status affects its production and operational activities, financing scale, and willingness to engage in TP. The ALR is a key indicator for assessing an enterprise's financial health and often affects its ability and willingness to invest in TP. To erase the impact of corporate financial status, this study followed the Lan et al.'s (2024) and used the corporate asset-liability ratio as a control variable.

Mediating variable

Operating expenses (OE): From the above theoretical analysis, TP in enterprises is often accompanied by an increase in operating costs. These costs, directly or indirectly caused by technological advances, may include the purchase of new equipment, new systems, and the introduction of new platforms. To more accurately assess the impact of TP on FOP, this study adopted the approach of Hua et al. (2015) and used operating expenses as a mechanism variable. To standardize the dimensions, this study adopted the ratio of operating expenses to operating revenue as a standardized measure of OE.

Labor cost (LC): Given that manufacturing enterprises usually introduce new technologies and equipment while pursuing TP, they often need to recruit employees with higher technical capabilities to ensure the efficient use of these new technologies and equipment. Therefore, an enterprise's TP often leads to an increase in employee wages and salaries. However, whether salary growth positively influences manufacturing firms' overall added value requires further exploration. To systematically understand this mechanism and build on existing research (Armstrong et al., 2024), this study used employee compensation as a mechanism variable to analyze how TP influences the manufacturing industry's development. To standardize the dimensions, the ratio of labor cost to operating revenue was adopted as a standardized measure of LC.

Productive capacity (PDC): This refers to TP through the introduction of new technology, equipment, and technical personnel to improve the technical level. Enterprises' TP will often improve their production scale and speed, that is, improve their overall production capacity. Therefore, a better understanding of whether technological advances increase production efficiency and, in turn, business output is necessary. This study used the industrial sales output value as an intermediary variable to assess the production capacity of an enterprise (Guariglia et al., 2011). The PDC was logarithmized to standardize the units of the variables.

Moderator variable

Quality competitiveness (QCI): The above theoretical analysis shows that the industry QCI may have a regulatory effect between TP and enterprise output. To this end, this study introduced the QCI of each manufacturing industry in the "National Manufacturing Quality Competitiveness Index Communique" issued by the General Administration of Quality Supervision, Inspection, and Quarantine of the People's Republic of China. The index has the characteristics of strong authority and is comprehensive, comprising six core three-level indicators covering the standard and technical level, quality management level, quality efficiency and safety level, research and development and technology transformation ability, core technology ability, market adaptability, and other dimensions. Therefore, this study introduced industry QCI as a regulatory variable to describe the development mechanism of TP and enterprise output.

Description of variables

Table 1 lists the summary statistics of the basic variables. The FOP ranges from 0.000 to 19.741, with a standard deviation of 1.876, suggesting significant variation in output across enterprises. Similarly, the logarithmic value of TP ranges from 0.000 to 8.681, reflecting considerable differences in enterprises' technological capabilities.

Model specification

This study developed nonlinear panel regression models, including those with mediating and moderating effects, to examine the nonlinear impact and pathways between TP and FOP.

Benchmark regression model

To explore the nonlinear link between TP and FOP, this study

Table 1
Statistics description of variables.

Variables	Observations	Mean	sd	min	max
EOP	958,059	10.175	1.876	0.000	19.741
TP	958,059	0.081	0.376	0.000	8.681
TP2	958,059	0.148	1.065	0.000	75.360
RFAE	958,059	5.119	0.722	3.816	7.715
INDS	958,059	15.976	0.747	13.645	17.440
TTA	958,059	9.673	0.883	6.941	11.167
TTP	958,059	7.429	2.180	0.000	17.524
AGE	958,059	24.186	8.628	13.000	66.000
ALR	958,059	0.005	0.037	0.000	5.936
OE	958,059	0.085	0.082	0.001	0.460
LC	958,059	0.075	0.068	0.004	0.384
PDC	958,059	1.295	2.194	0.000	13.721
QCI	958,059	80.853	4.149	73.370	91.680

adopted Jin et al.'s (2021) method to develop a nonlinear panel regression model as follows.

$$FOP_{it} = \alpha_0 + \alpha_1 TP_{it} + \alpha_2 TP2_{it} + \alpha_3 X_{it} + \varepsilon_{it} \tag{6}$$

In Model (6), FOP_{it} is the output of enterprise i in year t; TP_{it} is the number of invention patents granted by the firm, that is, the TP of the enterprise; $TP2_{it}$ is the quadratic term of TP; X_{it} is the control variable; α_0 is the constant term; α_1 is the coefficient of TP; α_2 is the coefficient of TP2; α_3 is the coefficient for the control variable; and ε_{it} represents the random error term.

Mediating effect model

Based on Model (6), we referred to Hayes and Preacher (2010) and Jiang (2022) and introduced the following stepwise regression analysis framework:

$$M_{it} = \beta_0 + \beta_1 TP1_{it} + \beta_2 TP2_{it} + \beta_3 X_{it} + \varepsilon_{it} \tag{7}$$

In Model (7), M_{it} is the mediating variable, and the remaining variables have the same meanings as in Model (6).

Moderating effect model

In the above analysis, QCI moderated the relationship between TP and FOP. To clarify this moderating effect, we drew on Chen et al. (2023), introduced the following moderating effect model.

$$\mathrm{FOP}_{\mathrm{it}} = \alpha_0 + \alpha_1 \mathrm{TP}_{\mathrm{it}} + \alpha_2 \mathrm{TP2}_{\mathrm{it}} + \alpha_3 \mathrm{QCI}_{\mathrm{it}} + \alpha_4 \mathrm{TP}_{\mathrm{it}} \times \mathrm{QCI}_{\mathrm{it}} + \alpha_5 \mathrm{TP2}_{\mathrm{it}} \times \mathrm{QCI}_{\mathrm{it}} + \alpha_6 \mathrm{X}_{\mathrm{it}} + \varepsilon_{\mathrm{it}} \tag{8}$$

In Model (8), QCI is the moderating variable; α_3 is the coefficient of the moderating variable; $TP_{it} \times QCI_{it}$ is the interaction term of TP and the moderating variable; α_4 is its coefficient; $TP2_{it} \times QCI_{it}$ is the interaction term of the quadratic term of TP and the moderating variable; and α_5 is its coefficient. The other variables have the same meanings as in Model (8).

Results

Benchmark regression results

The benchmark regression results are illustrated in Table 2, illustrating how TP influences FOP in the manufacturing sector. In Column (1), the coefficients of TP and TP2 are both significant at the 1 % level, with values of −4.385 and 3.090, respectively, confirming a "positive U-shaped" relationship between TP and FOP, thus validating Hypothesis 1. In Column (4), after incorporating all control variables, year controls, and firm fixed effects, TP remains significantly negative at the 1 % level, while TP2 remains significantly positive at the 1 % level, further reinforcing Hypothesis 1. The reason for this phenomenon may be that, in the early stages of TP, enterprises incur large costs owing to their technological innovation activities. However, at this stage, the production scale of enterprises adopting new technologies is small, and their production efficiency and relative returns are low, resulting in a negative effect of TP on enterprise growth. Furthermore, as TP continues to deepen, the production scale of firms applying new technologies increases, and the marginal revenue gradually exceeds the marginal cost, further promoting the growth of enterprise output.

Table 2
Benchmark regression results.

Variables	(1) FOP	(2) FOP	(3) FOP	(4) FOP
TP	−4.385***	−4.415***	−5.178***	−5.729***
	(0.473)	(0.473)	(0.681)	(0.677)
TP2	3.090***	3.089***	3.444***	3.972***
	(0.800)	(0.799)	(0.909)	(0.922)
RFAE		−2.298***	−2.366***	−1.483***
		(0.231)	(0.271)	(0.199)
INDS		0.503***	1.030***	0.896***
		(0.179)	(0.187)	(0.220)
TTA			0.318***	0.738***
			(0.079)	(0.285)
TTP			0.196***	0.104***
			(0.032)	(0.035)
AGE				−0.009*
				(0.005)
ALR				0.871**
				(0.425)
Constant	−0.375***	2.401	−9.751***	−15.141***
	(0.057)	(3.085)	(3.258)	(3.414)
Year FE	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES
Observations	958,059	958,059	958,059	958,059
R-squared	0.029	0.30	0.033	0.050

Notes: Robust standard errors are in parentheses; *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$, the same as below.

Robust test

U-shaped test

To test the relationship between TP and FOP, we followed Lind and Mehlum (2010). The U-shaped effect was proved, and the results are presented in Table 3. The U-shaped test indicated that the lower-bound slope (−7.256) and upper-bound slope (92.583) of TP are both significant at the 1 % level. The critical point of the U-shaped curve is approximately 0.631, which is within the sample value range. Similarly, the Sasabuchi-Lind-Mehlum test dismissed the null hypothesis. These findings validate the U-shaped link between TP and FOP, further reinforcing the robustness of the baseline regression findings.

Table 3
U-shaped relationship test results.

Variables	Result
Data range	[0.000, 8.681]
Lower bound slope	−7.256***
Upper bound slope	92.583***
Sasabuchi-Lind-Mehlum Test for a U-shape relationship	76.60***
Extreme point	0.631

Lind and Mehlum (2010) proposed three steps to verify the U-shaped relationship. First, the quadratic coefficients must be significant and consistent with theoretical expectations. Second, a slope difference between X and Y should exist within the sample value range. Finally, the extreme point should be within the value range of the independent variable. The baseline findings validate that the quadratic coefficient is significantly consistent with theoretical expectations. The U-shaped test results indicate that the extreme point falls within the value range of the TP. Therefore, this study introduced the scatter plot of TP and FOP, as shown in Fig. 2. As Fig. 2 shows, TP and FOP exhibit significant slope differences across the sample value range. In summary, the nonlinear relationship between TP and FOP is verified.

Change variable test

To assess the reliability of the baseline results, we conducted robustness checks by substituting TP with the aggregate count of granted patents.. As presented in Column (1) of Table 4 reveal that after replacing the core explanatory variables, the first-order term of TP is significant at the 1 % level with a positive coefficient, while the quadratic term of TP is significant at the 1 % level with a negative coefficient. These findings indicate that the "positive U-shaped" relationship between TP and FOP maintains a certain level of robustness.

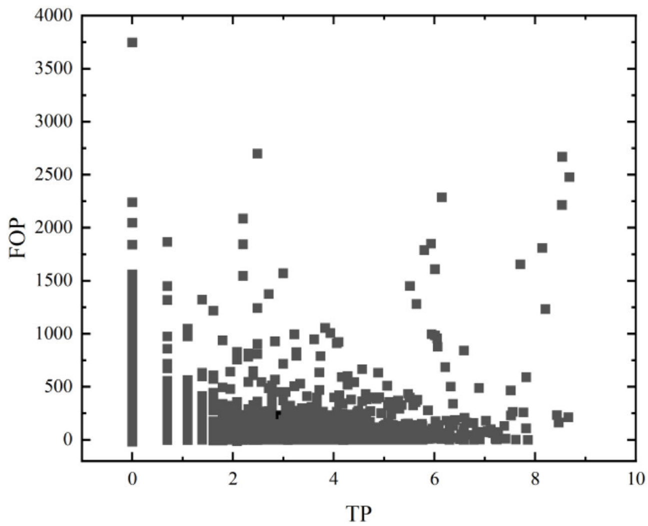

Fig. 2. The scatter plot of TP and FOP.

Winsorization test

To enhance the robustness of the baseline regression findings, and mitigate the impact of extreme values, we followed Li et al. (2022) by winsorizing the sample data at the 1 % level and incorporating them into Model (6) for testing. The detailed regression outcomes are listed in the Column (2) of Table 4. They reveal that after adjusting for potential outliers, the coefficient of TP remains significantly negative, while the coefficient of TP2 remains significantly positive, thus supporting the "positive U-shaped" relationship between TP and FOP. This results confirm the robustness of this study's benchmark regression results.

Change sample data

To further verify the robustness of the baseline regression results, we substituted the sample data for a re-evaluation. Although China's industrial enterprise data are the most authoritative statistical data in the country, their statistical period is limited. To compensate for the estimation bias caused by a possible sample time delay in the benchmark regression sample data, we incorporated data from China's A-share listed manufacturing companies from 2007 to 2023 to conduct a robustness test. We obtained 19,726 enterprise data points and introduced them into Model (6) for testing. As evidenced by Column (3) of Table 4, the coefficients of TP and TP2 remain significant after substituting the data, with signs consistent with the benchmark regression findings.

Change estimation model

To test the robustness of the nonlinear estimation in the baseline regression, the panel smooth transition regression (PSTR) and machine learning least absolute shrinkage and selection operator (LASSO) models were used to re-test the sample data. The PSTR method provides a more flexible nonlinear approach to capture the nonlinear relationship between TP and FOP, addressing the possibility that the relationships between variables may change gradually and allowing for a gradual transition between different stages of TP. The LASSO method helps identify the most important variables in high-dimensional datasets, improving the accuracy and interpretability of the model while preventing overfitting. Together, these two methods effectively identified the relationship between TP and FOP. The test results of the PSTR are listed in Column (4) of Tables 4 and 5. In the PSTR model, a TP-nonlinear variable is used to capture the nonlinear effect; its value is significantly nonzero, indicating that the nonlinear part has a significant influence on the dependent variable (Zhang et al., 2021). According to the results in Column (4) of Table 4, there is a significant nonlinear effect between TP and FOP. The reliability test results for the PSTR model are presented in Table 5. The results show that the AIC and SC values of the PSTR model are lower than those of the traditional nonlinear Model (6), and the LM test statistic is significantly below 0.05. In summary, a nonlinear effect exists between TP and FOP, which further improves the reliability of the benchmark regression results. To better capture the nonlinear effect between TP and FOP, we de-meaned the samples and introduced them into the LASSO model for testing (Belloni et al., 2014). The findings show that after removing the mean and replacing the test model, TP-demeaned is significantly negative and TP2-demeaned is significantly positive. This aligns with the baseline regression results and

Table 5
PSTR validity test results.

	PSTR method	Traditional nonlinear model
AIC	5,281,674	5,283,002
BIC	5,281,835	5,283,140
LM test result	0.000	–

Table 4
Robustness test results.

Variables	(1) Change variable FOP	(2) Winsorization FOP	(3) Change sample data FOP	(4) PSTR model FOP	(5) LASSO model FOP
TNPG	−5.771*** (0.079)				
TNPG2	2.588*** (0.026)				
TP		−0.107* (0.058)	−0.010** (0.005)	−7.840*** (0.421)	
TP2		0.577*** (0.049)	0.002* (0.001)		
TP-nonliner				12.444*** (0.463)	
TP-demeaned					−3.606*** (0.160)
TP2-demeaned					2.595*** (0.060)
Constant	−12.397*** (0.509)	−3.816*** (0.246)	2.362*** (0.268)	−15.245*** (1.913)	0.708*** (0.160)
Control FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES
Observations	958,059	958,059	19,726	958,059	958,059
R-squared	0.269	0.419	0.863	0.206	–

confirms their robustness.

Endogeneity test

Given the possible omitted variables in the variable selection process and reverse causality, the benchmark regression results may have endogeneity problems. To mitigate potential endogeneity issues, we drew on Zheng et al. (2024) and used the industry-level averages of TP (Mean-TP) and TP2 (Mean-TP2) from other firms in the same sector as instrumental variables. This variable selection not only considers the endogeneity of variable selection but also more intuitively reflects the impact of TP on FOP. Furthermore, following Liu and Lee's (2013) approach, we employed the two-stage least squares (IV-2SLS) method to re-estimate the variables. Table 6 presents the results. In the first-stage regression, the coefficients of the instrumental variables are significantly positive, and the Wald F-statistic is 295.060, which is significantly greater than the critical point of 10 %, suggesting the absence of weak instrumental variables. The LM statistic is 589.670 ($P = 0.000$), rejecting the null hypothesis that the instrumental variables could not be identified and confirming the appropriateness of the selected instrumental variables for the endogeneity test. Moreover, the test results in Column (3) of Table 6 align with the benchmark regression results, further validating the "positive U-shaped" relationship between TP and FOP.

Heterogeneity analysis

Heterogeneity based on technology intensity

Based on the above analysis, TP's impact on FOP may significantly vary based on the firm's technology intensity. We drew on the methods of Yang et al. (2024) and, according to the provisions of the OECD bilateral trade database (OECD), divided the sample data into high and low-technology-intensive enterprises and brought them into Model (6) for testing. The test results are listed in Table 7. Columns (1) and (2) present the results of the impact of TP on the output of high- and low-tech firms, respectively. The results show that TP's coefficient is significantly negative and the TP2's coefficient is significantly positive in high enterprises and low-technology-intensive enterprises, confirming a "positive U-shaped" relationship between TP and FOP. It should be emphasized that the TP coefficient of high-technology-intensive enterprises is −4.494, and the TP2 coefficient is 2.861. The TP coefficient of low-technology-intensive enterprises is −15.463, and the TP2 coefficient is 11.107. The coefficient difference between the TP groups is −7.02, indicating that the negative effect of early TP is more significant in low-technology-intensive enterprises. High-technology-intensive enterprises usually have stronger R&D capabilities, higher technology accumulation, faster industry updates, more targeted R&D activities, and more effective resource allocation. Therefore, TP has a lower inhibitory effect on the early output of high-technology-intensive enterprises. However, the TP behavior of low-technology-intensive enterprises may have a greater impact on FOP. The main reasons for this are that low-technology-intensive enterprises have problems such as a slow industry update speed, poor technology absorption capacity, and insufficient employee skills. In the early stages of TP, more funds must be invested in equipment upgrading and personnel training, resulting in lower efficiency in the benefit conversion of TP. The coefficient difference between the TP2 groups is 5.688, indicating that low-technology-intensive enterprises have higher potential returns after the deepening of TP because they can gradually bridge the technological gap through imitation and introduction. After technology accumulation, they can release higher production potential and enjoy a "late-mover advantage." In summary, Hypothesis 2 has been verified, and the impact of TP on FOP shows significant heterogeneity depending on the enterprises' degree of technology intensity.

Table 6
Endogeneity test results.

Variables	IV First stage		IV Second stage
	(1) TP1	(2) TP2	(3) FOP
Mean-TP	0.882***	−0.070***	
	(0.056)	(0.158)	
Mean-TP2	0.073***	1.064***	
	(0.025)	(0.072)	
TP			−6.595***
			(0.892)
TP2			3.649***
			(0.783)
Constant	−0.027	−0.001	7.226***
	(0.154)	(0.005)	(9.903)
Control FE	YES	YES	YES
Year FE	YES	YES	YES
Firm FE	YES	YES	YES
Observations	958,059	958,059	958,059

Heterogeneity based on firm age

A firm's age is an important indicator of its production and operational activities. According to the life cycle theory, firms in different age stages tend to have different operational modes and innovation behaviors. To better verify the heterogeneous effect of enterprise age heterogeneity on enterprise TP, we referred to Gao et al. (2024) and divided the enterprises into the "older age" group and "younger age" group according to the years of incorporation of listed enterprises. Column (3) of Table 7 presents the test results for older age firms, indicating a "positive U-shaped" link between TP and FOP in this group. However, according to the "younger" group of firms reported in Column 2, the impact of TP and TP2 on FOP is not significant. Additionally, the coefficient difference between the TP groups was 5.533, and that between the TP2 groups was −3.155. The main reason for this phenomenon may be that older enterprises have accumulated rich resources due to long-term operations, including capital, technical reserves, management experience, and anti-risk ability, which can effectively cope with the adjustment cost in the early stages of TP. Therefore, enterprises in the older group show a significant negative effect in the early stage of TP but a strong positive benefit in the later TP stage, forming a "positive U-shaped" relationship. Young firms often play the role of "followers" in the industry. Their R&D capabilities tend to be weak, and they tend to imitate the development of older companies. Owing to the short establishment time and limited accumulation of resources, enterprises face greater financial pressure and management challenges in the TP process, and the positive impact of TP on output is difficult to demonstrate. The results confirm Hypothesis 2 that there is significant heterogeneity between the effect of TP on FOP and firm age.

Heterogeneity based on region

The nonlinear impact of TP on FOP may vary depending on a company's location. According to the "Opinions on Implementing the Policy Measures for the Development of the Western Regions" issued by the State Council, China is divided into the Eastern, and Central and Western Economic Zone (Lin et al. (2024)). The two economic zones significantly differ in terms of resource accessibility, policy support, talent development, and business environment. Columns (5) and (6) of Table 7 show the results for testing regional differences in the effect of TP on FOP, indicate that TP has a significant negative effect, whereas TP2 has a significant positive effect. Notably, the absolute coefficient for the Central and Western region is greater than that for the Eastern region. The coefficient difference between the TP groups is 0.051, while the coefficient difference between the TP2 groups is −0.025, indicating significant heterogeneity in the impact of TP on FOP across different regions, which may be attributed to several factors. The Eastern region has a higher level of economic development, better infrastructure, and superior innovation resources. Specifically, the Eastern region is the economic backbone of China and has received substantial policy support, including favorable industrial policies and financial incentives to

Table 7
Heterogeneity test results.

Variables	(1) High-tech firms FOP	(2) Low-tech firms FOP	(3) Older age firms FOP	(4) Younger age firms FOP	(5) Eastern region FOP	(6) Central-western regions FOP	(7) High innovation policy environment FOP	(8) Low innovation policy environment FOP
TP	−4.494***	−15.463*	−6.622***	0.319	−3.813***	−12.400**	−4.496**	−6.664**
	(0.072)	(0.127)	(1.948)	(0.311)	(1.129)	(5.987)	(1.744)	(2.981)
TP2	2.861***	11.107**	4.502***	0.152	2.963***	7.525**	3.424***	4.437***
	(0.531)	(5.203)	(1.069)	(0.165)	(0.567)	(3.405)	(0.885)	(1.683)
Constant	−21.839***	71.379***	−14.914***	−11.770***	−13.357***	−17.030*	−15.516***	−12.152***
	(4.252)	(19.060)	(4.261)	(3.891)	(3.801)	(8.738)	(5.135)	(3.310)
Control FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES
Observations	439,933	518,126	740,603	217,456	653,796	304,263	491,543	466,516
R-squared	0.045	0.096	0.045	0.245	0.200	0.250	0.211	0.078
TP IGCD	−7.020***		5.533*		0.051**		0.040**	
TP2 IGCD	5.688***		−3.155**		−0.025**		0.032**	

Note: IGCD is the test result of the inter-group coefficient difference in the heterogeneity analysis, which was obtained using a permutation test of 1000 bootstrap samples.

encourage innovation, resulting in a strong willingness for firms to innovate. Simultaneously, the Eastern region's economic prosperity fosters a well-developed talent training system, making it easier for firms in this area to attract specialized talent, which contributes to technological advancement. Thus, the inhibitory effect of TP on firms' innovation capabilities in the Eastern region is relatively small. However, owing to firms in the Eastern region have already reached a high level of technological development, the marginal benefits of TP2 have a limited positive effect on FOP. Conversely, in the Central and Western region, a lower level of economic development, inadequate infrastructure, and less-developed talent training mechanisms lead to a weaker attraction for talent, resulting in limited TP resources for firms. This makes it difficult for firms in these regions to realize significant technological benefits in the short term. In the early stages of TP, firms in the Western region face higher costs and are constrained by insufficient innovation resources and weak R&D capabilities, and the benefits of TP are released slowly and may be offset by initial costs. Nevertheless, owing to the relatively low level of technology in the Central and Western region, TP can significantly bridge the existing technology gap. Consequently, the positive effect of TP2 on output is comparatively strong. These results validate Hypothesis 2.

Heterogeneity based on innovation policy environment

Regional government R&D support was calculated according to the ratio of regional government R&D expenditure to regional GDP, and enterprises were divided into those with high-innovation policy environments and those with low-innovation policy environments according to the average value. The test results are presented in Columns (7) and (8) of Table 7. The results show that the absolute values of TP and TP2 coefficients of enterprises in low-innovation policy environments are greater than those in high-innovation policy environments. The coefficient difference between the groups showed that the coefficient difference between the TP groups was 0.04**, and the coefficient difference between the TP2 groups was 0.032**. The reason for this phenomenon may be that the government strongly supports enterprise innovation in high-innovation policy environments and provides enterprises with more financial and R&D subsidies. Companies in such environments may rely on external support and resources, reducing their drive for self-innovation. The TP of such enterprises is often gradual and subject to policy-oriented innovation, resulting in a relatively flat marginal effect of TP, which is reflected in the small difference between TP and TP2. In low-innovation policy environments, companies may face less government support and fewer resources and, therefore, must rely on their own innovation capabilities to remain competitive. Enterprises are often more motivated to innovate and are willing to invest in TP. Additionally, companies may be in a highly competitive market environment and must maintain a competitive advantage through innovation. The low-innovation policy environment may force firms to pay more attention to long-term technological innovation and efficiency improvement, and this competitive pressure pushes firms to make more technological breakthroughs, thus manifesting in larger differences in the TP and TP2 coefficients. Hypothesis 2 is verified.

Further analysis

Mediating effect test of operating expenses

Maintenance and operating costs are crucial factors that affect a firm's development. However, the effect of technological innovation on operating expenses remains unclear. Therefore, this study incorporated the firm's operating expenses into Eq. (7) for testing, listed in Column (1) of Table 8. Column (1) indicates that the TP's coefficient is significantly positive, with a value of 0.006. This suggests that during the early stages of TP, innovation costs are high and operational efficiency is low, significantly increasing the firm's operating costs. However, the coefficient of TP2 is significantly negative at −0.001, indicating that as the firm's technology matures, TP contributes to reducing operating expenses. This may be because, at this stage, technological progress improves overall production efficiency, thereby lowering operational costs. According to Barney (1991) and Bloom et al. (2012), operating expenses are significantly negatively correlated with firm performance. High operating costs may suppress profits in the short term; however, in the long run, firms can build a competitive advantage through technological accumulation, ultimately improving their output. This supports Hypothesis 3a, demonstrating that TP influences firm development by

Table 8
Mechanism test results.

Variables	(1) OE	(2) LC	(3) PDC
TP	0.006***	0.013***	−0.011*
	(0.001)	(0.001)	(0.006)
TP2	−0.001**	−0.002***	0.009***
	(0.001)	(0.001)	(0.002)
Constant	0.704***	0.141***	8.186***
	(0.009)	(0.003)	(0.082)
Control FE	YES	YES	YES
Year FE	YES	YES	YES
Firm FE	YES	YES	YES
Observations	958,059	958,059	958,059
R-squared	0.030	0.046	0.125

affecting operating expenses.

Mediating effect test of labor costs

According to the theoretical analysis, a firm's TP behavior is constrained by operating and labor costs. To test whether labor costs mediate the effect of TP on firm development, we introduced labor costs per unit of output as a mediator variable. Column (2) of Table 8 lists the results. As shown in Column (2), TP markedly elevates labor costs, indicating that, in the early stages of TP, each unit increase in TP leads to a 1.3 % increase in unit labor costs. This phenomenon may be attributed to the need for firms to enhance employee skills to match production requirements, such as hiring highly skilled talent or providing relevant training, which increases labor costs to some extent. However, the coefficient of TP2 is −0.002, suggesting that in the later stages of TP, as production efficiency improves, unit labor costs begin to decrease. According to Acemoglu (2002) and Hellerstein et al. (1999), while TP initially amplifies skilled labor demand and escalates labor costs, the subsequent integration of complementary competencies optimizes output efficiency, thereby reducing unit expenditures during prolonged implementation. This forms a "cost increase-efficiency increase-output increase" effect. These findings further validate Hypothesis 3b, which states that TP influences firm development through its impact on labor costs.

Mediating effect test of production efficiency

A firm's production efficiency affects both its production costs and output. Specifically, TP improves production efficiency, which drives firm growth. This study drew on Guariglia et al.'s (2011) method of introducing industrial sales value as a mediating variable for testing. Column (3) of Table 8 shows that TP is significant, with a coefficient of −0.011, indicating that production efficiency is suppressed in the early stages of TP. This is because the initial application of new technologies often involves extensive debugging, which consumes significant production time and leads to a temporary decline in production efficiency. However, TP2 is significantly positive, with a coefficient of 0.009, suggesting that as firms' TP improves, production efficiency increases. Barney (1991) and Solow (1957) found that, in the early stages of technological progress (TP phase), resources are consumed during the debugging and adaptation process, which temporarily hinders production efficiency. Yet, as technology matures (TP2 phase), firms experience an efficiency boost through the reorganization of production factors and the "learning by doing" effect, thus driving output growth. This conclusion supports Hypothesis 3c of the paper, which posits that production efficiency mediates the relationship between TP and firm development.

Moderating effect test of quality competitiveness

According to the above theoretical analysis, industrial QCI significantly impacts enterprise development in an endogenous economic growth model. Therefore, this study introduces the industry QCI related to firms and examines the impact of QCI progress on firm development. The detailed test results are presented in Table 9 and Fig. 3. Table 9 demonstrates the coefficient of the interaction term between QCI and TP is −0.073, indicating that QCI has a suppressive effect in the initial stage of TP. In the early stages of TP, to achieve higher internal quality standards, firms need to invest more resources alongside TP, such as higher production costs and stronger quality control capabilities, which put greater economic pressure on them. This means that, in the initial stage of TP, firms may experience prolonged output stagnation due to increased investments. The interaction term coefficient between QCI and TP2 is 0.049, indicating that QCI contributes positively in the later stages of TP. As TP deepens and the benefits of technology become apparent, firms can promote progress in QCI by enhancing technical standards and optimizing production processes. Companies are better able to absorb the high costs associated with TP, and once the technology matures, they can effectively improve production efficiency and product quality, thereby increasing overall output. As Fig. 3 shows, quality competition serves as a positive moderating role in the process through which TP affects a firm's development. In the early stages of TP, enterprises may need higher investments to meet the requirements of QCI, thus amplifying the negative impact of TP. In the later period of TP, industrial QCI fosters a more favorable setting for TP achievements, and the existence of a quality price difference enhances the positive effect of TP on FOP, confirming Hypothesis 4. These results reveal the dual role of QCI in the relationship between TP and FOP. Initially, this may increase the burden of TP for firms by suppressing FOP growth. However, as technology matures, the QCI helps firms better cope with the challenges posed by TP, ultimately driving significant increases in FOP.

Table 9
QCI moderation effect test results.

Variables	TOP
TP	−1.835***
	(0.079)
TP2	0.077***
	(0.006)
QCI	−0.036***
	(0.008)
TP × QCI	−0.073***
	(0.002)
TP2 × QCI	0.049***
	(0.001)
Constant	−13.762***
	(2.114)
Control FE	YES
Year FE	YES
Firm FE	YES
Observations	958,059
R-squared	0.201

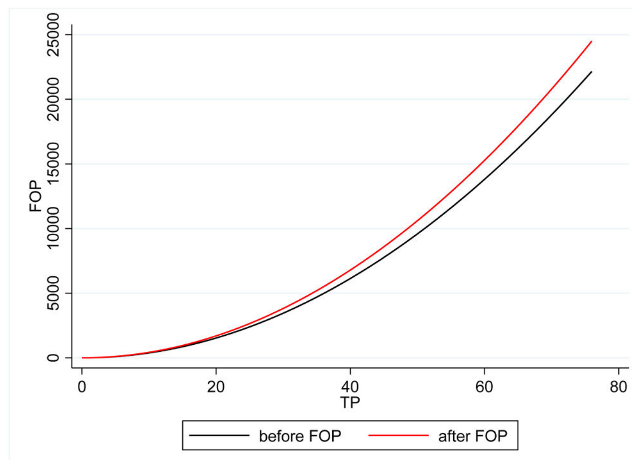

Fig. 3. The moderating effect of QCI.

Conclusions

Discussion and analysis

This study empirically analyzed TP's influence on FOP based on data from Chinese industrial firms and A-share-listed companies. Specifically, the early stages of TP are characterized by increased costs and reduced efficiency, exerting a crowding-out effect on FOP. Conversely, the later stages witness improvements in production processes and operational efficiency, which subsequently enhance FOP. These results emphasize the need to consider the dynamic nature of enterprise performance and the lagged effects of TP on such performance.

Furthermore, this study elucidates the mediating roles of operational costs, labor costs, and production efficiency in this relationship. During the initial phase of technology adoption, substantial investments, such as the deployment of new production lines, lead to rising operational costs and diminished output. However, as firms achieve technological maturity, their operational costs decline and drive subsequent output growth. Similarly, to meet TP requirements, firms invest in employee training and recruit skilled personnel, resulting in elevated labor costs that temporarily suppress output. As technological integration stabilizes over time, labor costs decrease, thereby fostering output expansion. Productivity serves as a key mediating variable, indicating that enterprises must adapt to the introduction and assimilation of new technologies. Productivity may be constrained in the early stages of technological adoption, thereby inhibiting output growth. However, with an increase in technological maturity, productivity gains significantly enhance corporate output.

Additionally, this study highlights the moderating role of QCI in the relationship between TP and FOP. In the early stages of TP, QCI acts as a negative moderator, amplifying the costs of TP by requiring additional investments in quality control and production standards. However, as TP matures, QCI plays a positive moderating role, enabling firms to leverage their TP to enhance product quality and production efficiency, which in turn boosts overall output. This dual effect of QCI emphasizes the role of industry-specific factors in influencing TP's outcomes.

Practical implications

Based on the above findings, we propose the following policy recommendations:

First, a comprehensive TP evaluation system should be established. Firms should be actively guided in developing a comprehensive TP system. This system should primarily include metrics such as R&D investment intensity, the proportion of R&D personnel, the speed of new product development, and the ability to absorb and transfer external technologies. This will effectively assess the level of TP within firms and its nonlinear impact on FOP. During this process, the government should provide an online technology consultation platform for professional advisory services and assist firms in establishing evaluation systems. However, the challenges in implementing this policy include potential flaws in the design of TP evaluation systems. Additionally, establishing the online technology platform may lead to personnel allocation issues. The feasibility of this policy mainly depends on government-business cooperation, phased implementation, and gradual improvements in personnel allocation to ensure smooth policy execution.

Second, we provide differentiated innovation support policies for different types of firms at various stages of TP. To alleviate the initial suppressive effect on low-tech-intensive firms at the early stage of TP, offer a higher proportion of financial subsidies or pre-tax deductions for project expenditures at this initial stage. Regarding TP support for firms in the Central and Western regions, the government can adopt a tiered support strategy based on factors such as firm size, technological level, and market potential. Simultaneously, the government can establish targeted technological transformation subsidy policies based on the TP needs at different firm stages. Potential challenges to the feasibility of implementing this support policy include financial sustainability and resource allocation imbalances. Specifically, there is a risk of misclassification when categorizing heterogeneous firms and policies, which may lead to subsidy deviations. Moreover, an excessive fiscal burden places considerable financial pressure on the government. Therefore, to ensure the feasibility of this policy, strict project evaluation and supervision mechanisms must be established to ensure accurate policy execution, ensuring that larger firms can receive higher levels of funding support while small and medium-sized enterprises can gain corresponding support through lower application thresholds.

Third, quality management and brand-building capabilities should be enhanced. The government should provide financial support to companies to obtain international quality certifications (e.g., ISO 9001), reduce the economic costs associated with applying for such certifications, and help firms improve their quality management and brand-building capabilities. Moreover, the government should establish quality awards to encourage firms to enhance their quality improvement efforts and build their market reputation. Additionally, the government should regularly organize quality management training courses covering topics such as quality control, production process optimization, and international quality standards. These courses will help managers and technical staff acquire advanced international quality management concepts and practices, thereby effectively improving firms' quality management capabilities. Potential challenges to implementing this policy include high certification costs for small and medium-sized enterprises and low willingness to participate. The feasibility of this policy mainly depends on the government providing quality management consulting services to help firms understand certification processes and quality management practices, organizing regular training and guidance sessions, reducing initial financial and knowledge barriers, offering long-term subsidies or tax incentives to lower costs, promoting successful role models, and increasing firm participation. For example, Gree Electric Appliances Inc. obtained ISO 9001 certification in 1996 and closely integrated technological innovation with quality management. Through continuous technological advancements, Gree improved its product quality and won several national quality awards. According to public data, by 2009, Gree became the leader in China's air conditioner market. As of 2023, Gree still holds the highest market share in online retail for air conditioners, with both export quantity and scale remaining industry-leading.

Fourth, a dynamic market assessment and feedback mechanism should be established. It is crucial to consider the ongoing impact of TP and market environment changes on firm development. The speed and depth of TP and market changes may have varying effects on a firm's production, operations, and competitive landscape. Therefore, the government must not only focus on the current needs of firms but also be equipped with a flexible adjustment mechanism to respond to future changes. The government should establish a regular evaluation and dynamic adjustment system and update policy tools and implementation methods in a timely manner based on the pace of technological progress and changes in the market environment. With the emergence of new technologies, the direction and content of government support must be adjusted accordingly. Given the industry consolidation and market competition changes that technological progress may bring, the government should strengthen interdepartmental coordination, particularly in areas such as science and technology, finance, industry, and education. For example, fiscal subsidies, tax incentives, and technology transfer policies can be coordinated across different policy departments to ensure coherence and effectiveness of policy implementation.

Although the research design is based on data from China, its core principles—the dynamic evaluation of technological stage differences and the strengthening of QCI—can provide a framework for other economies. The nonlinear pattern of technological progress reflects the dynamic process through which firms move from technology absorption to independent innovation, which aligns with the predictions of the technology life-cycle theory. Despite developed economies having a more advanced technological base, their industrial upgrading stages also experience a nonlinear impact of TP on FOP (Bloom et al., 2012). Therefore, the findings of this study do not depend on a specific institutional environment and have theoretical applicability across economies.

The findings of this study apply to the following types of economies: countries with deep government involvement in innovation systems, where technology subsidies and special fund policies are similar to China's model and firms face comparable resource allocation and policy response mechanisms; emerging markets in the technology catch-up phase, where firms face similar early-stage suppression effects, such as high R&D costs and low technological absorption capacity, and require differentiated policy support; and large economies with regional development imbalances, where significant internal disparities exist, necessitating targeted support for firms at different levels of technological development.

Limitations and outlook

This study provides theoretical support for enterprise growth in other emerging economies and serves as a reference for countries in formulating precise and well-founded development strategies and policies. In future research, the scope of the study should be expanded, and efforts should be made to cooperate with scholars from different countries to obtain more diverse data sources and test the generalizability of the research findings. Additionally, future studies can delve deeper into the nonlinear relationships among TP, QCI, and enterprise development and study the specific impacts of different policy environments on the development of the manufacturing industry to provide more systematic and comprehensive theoretical guidance and practical suggestions for sustainable enterprise growth. In terms of research on nonlinear relationships, future studies could employ more advanced econometric models to explore the nonlinear link between TP and FOP in greater depth. For example, methods such as support vector machines and random forests can be combined to more accurately capture these complex nonlinear effects, thereby providing systematic and comprehensive theoretical guidance and practical suggestions for the sustainable growth of enterprises.

Original article statement

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CRediT authorship contribution statement

Ning Wang: Writing – review & editing, Writing – original draft, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Yuanyuan Hong:** Writing – review & editing, Writing – original draft, Software, Resources, Methodology, Investigation. **Ziyu Guo:** Writing – review & editing, Visualization, Validation, Supervision, Methodology.

Declaration of competing interest

The authors report no competing interests to declare.

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