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Enterprise intelligent investment and total factor productivity

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Abstract: This paper employs micro-level data on intelligent investment and total factor productivity (TFP) of Chinese enterprises from 2011 to 2022 to examine the impact of intelligent investment on TFP in micro enterprises. The findings indicate that intelligent investment significantly enhances TFP, with this effect varying based on enterprise ownership structure and the development level of product markets. Mechanism analysis reveals that intelligent investment promotes TFP by alleviating enterprises financing constraints. This study enriches the literature on the economic consequences of intelligent investment and the determinants of total factor productivity. It provides empirical evidence supporting the intelligent transformation and high-quality development of enterprises.

1. Introduction

The report of the 20th National Congress of the Communist Party of China highlights that China's economy has transitioned from a phase of rapid growth to one focused on high-quality development. In this new stage, enhancing TFP and strengthening economic innovation and competitiveness are crucial for improving economic quality. Effectively utilizing intelligent investment to boost TFP and achieve long-term competitive advantage is not only essential for internal enterprises efficiency but also reflects the rational use of resources and advancements in innovation and technology.

Existing studies on the relationship between digital transformation, the digital economy, and TFP have been limited to manufacturing firms. There is a lack of systematic empirical research on how intelligent investment specifically impacts TFP, particularly in the context of advancing AI and big data technologies. This study aims to address this gap. We conducted an empirical analysis using data from Chinese A-share listed companies from 2011 to 2022, revealing that higher levels of intelligent investment are associated with increased TFP. Heterogeneity analysis showed that the effects of intelligent investment on TFP vary based on firm ownership structure and market development. Additionally, we examined the mechanisms through which intelligent investment influences TFP, finding that it initially increases financing constraints, which can subsequently reduce investment in intelligent technologies and slow the rate of TFP improvement.

Based on the above analysis, this paper examines the impact of intelligent investment on TFP from the perspective of enterprise intelligent investment. The innovation of this article lies in: firstly, it enriches the research on the economic consequences of intelligent investment in enterprises. Secondly, this study broadens the research on the determinants of total factor productivity. Thirdly, this study reveals the mechanisms through which intelligent investment affects total factor productivity, providing a scientific basis for managers to develop relevant investment strategies.

2. Theoretical analysis and research hypothesis

2.1. Intelligent investment and enterprise total factor productivity

"Made in China 2025" emphasizes that intelligence is the core technology of the new round of industrial revolution and a key step for China to transform from a manufacturing power to an intelligent manufacturing power [1]. Zhou (2015) found that intelligent manufacturing, as the core, covers information technology, biotechnology, new material technology and new energy technology, and widely penetrates and promotes the transformation of almost all fields to intelligence, green and service, constituting a group technological revolution, which marks the arrival of a new round of industrial revolution. As a key part of realizing intelligent transformation, enterprises must strengthen their investment in intelligence and improve their own intelligence level. Guo (2019) found that the improvement of AI services and the development of AI expansion technology will promote the flow of production factors between different industrial sectors, which indicates that increasing investment in intelligence will promote the development of AI technology and improve the total factor productivity of enterprises to a certain extent [2]. Intelligent investment stimulates the vitality of innovation within enterprises, promotes the development and promotion of new products and services [3], and the improvement of production methods and process optimization brought about by technological innovation can directly affect the improvement of total factor productivity. Zhao (2021) found that digital transformation can promote the improvement of total factor productivity by enhancing innovation capabilities, optimizing human resource allocation, promoting the integrated development of advanced manufacturing and modern service industries, and reducing costs [4].

Hypothesis 1: Higher levels of intelligent investment in enterprises promote total factor productivity.

2.2. Heterogeneity based on the nature of property rights

As SOE have an advantage over non-SOE in terms of resource allocation, and can mobilize capital and technology to support smart investment more flexibly, and local governments often have a strong incentive to support SOE in their jurisdictions and provide loan support to these enterprises by intervening in banks' credit decisions [5][6], thereby effectively improving production efficiency. According to the theory of new institutional organization, the survival and development of enterprises depends on the institutional environment, and the system will have a profound impact on the strategy, organizational structure and division of labor structure, and investment in new technologies, thereby affecting the total factor productivity of enterprises [7]. State-owned enterprises (SOE) may have unique advantages in terms of institutional organization and management, which can better integrate intelligent technology and internal processes to promote the improvement of total factor productivity. It can be inferred that state-owned enterprises (SOE) may have a better advantage in intellectual property protection and can better protect the technological innovations brought about by intelligent investments, thereby continuously improving productivity.

Hypothesis 2: In state-owned enterprises, higher investment in intelligent technologies more significantly enhances the improvement of total factor productivity.

2.3. Heterogeneity based on product markets

In areas where there is a lack of a sound product market system, it is difficult for enterprises to obtain the financial support needed for intelligent investment. This is due to the lack of an effective market system and property rights protection measures in the local product market, and firms tend to reduce their inputs [8]. In addition, the low level of development of the product market will lead to unclear product price formation mechanism, uncertainty in investment returns, and reduce the willingness of enterprises to invest. A sound product market system helps enterprises to more easily obtain the financial support they need for R&D. This system improves the efficiency of policy information transmission, reduces the information cost caused by the uncertainty of R&D projects, conveys confidence commitments to local governments and financial institutions, alleviates the doubts of external investors about enterprises innovation activities [9], and increases the feasibility of enterprise intelligent investment in R&D financing.

Hypothesis 3: In regions with more developed product markets, the effect of intelligent investment on enhancing corporate total factor productivity is amplified.

3. Research design

3.1. Sample Selection and data source

This paper selects Chinese listed companies from 2011 to 2022 as the research sample, and the data are derived from the China Stock Market &Accounting Research Database (CSMAR) and the China City Statistical Yearbook, and the original data are processed as follows: (1) The annual irregular transaction sample is excluded. (2) Exclude samples from the financial sector. (3) The samples with missing variable data in the main effect model were excluded. (4) All continuous variables in the main effect model were tailed by 1% or above. According to the above steps, 14,140 annual samples were finally obtained.

3.2. Empirical model

In order to demonstrate the first hypothesis of this paper: High levels of intelligent investment in enterprises promote total factor productivity. In this paper, the design model (1) is as follows:

$$TFP\_LP_{i,t} = \beta_0 + \beta_1 INT_{i,t} + \beta_n Control_{i,t} + e_{i,t}. \tag{1}$$

In model (1), $TFP\_LP_{i,t}$ is the total factor productivity of listed company i in year t, and the higher the value, the higher the total factor productivity of listed company i in year t. $INT_{i,t}$ is the intelligent investment level of listed company i in year t, the larger the value, the higher the investment in intelligent investment of listed company i in year t; If β_1 is significantly positive, it means that the higher the level of intelligent investment of the enterprise, the higher the total factor productivity of the enterprise, and the first hypothesis is true.

3.3. Variable measurement

3.3.1. Total factor productivity of enterprises

Existing literature employs five methods to calculate TFP: TFP_OP, TFP_LP, TFP_OLS, TFP_FE, and TFP_GMM. This study adopts the TFP_LP method, following the approaches by Levinsohn and Petrin (2003) and Lu and Lian (2012) [10][11], to measure firms' total factor productivity. The TFP_LP method captures the dynamics of productivity technology, specifically the impact of technological progress and changes on productivity. By utilizing the Luenberger productivity index, this approach provides a more accurate assessment of how technological changes affect productivity.

3.3.2. Enterprise intelligent investment

Referring to the research of Zhang(2022), Song(2022) and Qi(2020), Manually collect the amounts of intangible and fixed asset investments related to artificial intelligence in enterprises, and measure the level of intelligent investment using the ratio of the combined amount to the total annual assets [12][13][14].

3.3.3. Control variables

To control for potential model errors arising from firm characteristics, this study selects firm-level control variables as defined in Table 1.

Table 1: Variable Definition Table

Variable Type	Variable Symbol	Description of the variable
Explanatory variables	TFP_LP	It is calculated according to the calculation method proposed by Levinsohn and Petrin (2003), Lu and Lian(2012).
Explanatory variables	INT	Referring to the research of Zhang(2022), Song(2022) and Qi(2020)
Adjust variables	MI	This study refers to the work of Fan(2003), Wang(2019), and Yu(2010). For data values above the median, we assign 1; for those below or equal to the median, we assign 0.
	SOE	Assign a value of 1 to state-owned enterprises and 0 to non-state-owned enterprises.
Control variables	Size	The natural logarithm of total assets at the end of the period
	GROWTH	The sales growth rate, measured by the change in sales between T and T-1 divided by the sales in T year.
	LEV	The sales growth rate, measured by the change in sales between T and T-1 divided by the sales in T year.
	BOARDSIZE	The natural logarithm of the number of directors.
	BI	Proportion of independent directors on the board of directors.
	CASH	The ratio of net cash flow from operating activities to total assets.
	COMPANY_AGE	The natural logarithm of the number of years a business has been established +1.
	AGENCY	Overhead growth rate.
	GDP	The natural logarithm of the province's GDP per capita.
	MSALARY	The natural logarithm of the sum of the top three executive compensations.
	PPE	The ratio of net fixed assets at the end of the period to total assets at the end of the period.
	WCAPITAL	The ratio of total working capital to assets.
	CURRT	The ratio of current assets at the end of the period to current liabilities at the end of the period.
	ROA	Return on total assets.
	TOBINQ	Ending Market Value / Ending Total Assets.
	TAX	Comprehensive tax rate.
	FIN	The ratio of the output value of the financial industry to the GDP of the province.

4. Empirical result

4.1. Baseline regressions

Table 2 shows that In columns (1) and (2), the positive impact of intelligent investment on total factor productivity (TFP) is more significant for state-owned enterprises (SOE=1) compared to non-state-owned enterprises (SOE=0). This indicates that increasing intelligent investment enhances TFP across firms of different ownership structures, with a more pronounced effect in state-owned enterprises. Therefore, Hypothesis 1 is supported.

Table 2: Baseline regressions.

	(1)	(2)	(3)
	TFP_LP	TFP_LP	TFP_LP
INT	-0.240***	0.276***	0.302***
	(-4.30)	(8.86)	(3.94)
Con	no	yes	yes
Constant	7.648***	-6.963***	-6.965***
	(60.06)	(-40.14)	(-20.84)
Individual	no	no	yes
Ind	yes	yes	no
Year	yes	yes	yes
Observations	14,140	14,140	14,140
R2	0.225	0.824	0.771

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

4.2. Group test results

4.2.1. The nature of the property rights of the enterprise

Table 3: Results of grouping test of the nature of enterprise property rights and the development index of the local market

	(1)	(2)	(3)	(4)
	SOE=1	SOE=0	MI=1	MI=0
	TFP_LP	TFP_LP	TFP_LP	TFP_LP
INT	0.369***	0.189***	0.284***	-0.012
	(7.86)	(4.40)	(8.65)	(-0.11)
Con	yes	yes	yes	yes
Constant	-6.967***	-6.671***	-6.683***	-7.151***
	(- 20.76)	(-32.15)	(-11.28)	(-3.669)
Ind	yes	yes	yes	yes
Year	yes	yes	yes	yes
Observations	4,306	9,834	13,160	980
R2	0.833	0.810	0.829	0.829
Difference	0.18		0.272	
P-Value	0.0075***		0.0159**	

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

The state-owned enterprises were assigned a value of 1 and the non-state-owned enterprises were assigned a value of 0, and the regression test was grouped under the factors controlling the industry and year, and the results are shown in Table 3. In column (1), in the case of SOE=1, that is, in state-owned enterprises, the correlation coefficient between TFP_LP and INT is 0.369, which is significantly positive at the 1% level. In column (2), in the case of SOE=0, that is, in non-state-owned enterprises, the correlation coefficient between TFP and INT is 0.189, which is significantly positive at the 1% level, the difference between the two groups of coefficients is 0.18, and the coefficient difference t-test is 0.0075, which is significant at 1%, indicating that in enterprises with different industrial natures, increasing the level of intelligent investment will improve total factor productivity, but this effect is more significant in state-owned enterprises. Therefore, Hypothesis 2 is supported.

4.2.2. The market development index of the company's location

Table 3 show that in column (1), where MI=1 indicates regions with more developed markets, the impact of intelligent investment on total factor productivity is significantly positive at the 1% level. In column (2), where MI=0 indicates less developed markets, the correlation coefficient is -0.012 and is not significant. This suggests that in regions with more developed markets, increasing intelligent investment has a stronger positive effect on total factor productivity.Therefore, Hypothesis 3 is supported.

4.3. Results of mediating effect test

In practice, problems such as information asymmetry and agency costs lead to the inevitable waste of resources in the capital market, resulting in the external financing cost of enterprises being much higher than the cost of internal capital disposal. This cost difference leads to financing constraints, and the need for large amounts of capital support for firms' intelligent investment activities, which can limit their long-term development. On the one hand, some of the investment results of intelligence exist in the form of intangible assets and depreciate with the emergence of new technologies, and financial institutions tend to use physical assets as collateral for loans, making it difficult for enterprises to use intangible assets as collateral for loans. On the other hand, there are frictions in the real financial market, and firms are generally affected by financing constraints, which will affect firms' investment and R&D behavior. As a result, enterprises face difficulties in obtaining funds when making intelligent investments, especially due to financing constraints.

Table 4: Results of the mediating effect test

	(1)	(2)	(3)
	TFP_LP	KZ	TFP_LP
KZ			0.033***
			(7.58)
INT	0.276***	0.209***	0.269***
	(8.86)	(3.47)	(8.65)
Constant	-6.963***	3.584***	-7.082***
	(-40.14)	(10.69)	(-40.74)
Ind	yes	yes	yes
con	yes	yes	yes
Year	yes	yes	yes
Observations	14,140	14,140	14,140
R2	0.824	0.840	0.825

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

Therefore, we believe that a lower degree of financing constraints can provide financial support for enterprises' intelligent investment projects, which is conducive to the improvement of the level of intelligence and thus the improvement of enterprises' total factor productivity. To this end, this study follows the method of Kaplan and Zingales and introduces the KZ index (KZ) to measure the degree of financing constraints of firm i in year t. The KZ index is a positive proxy variable for financing constraints, where a higher value indicates that the firm faces more severe financing constraints. As shown in Table 4, the sample used for the mediation effect analysis is consistent with that of the main regression.

4.4. Robustness test results

4.4.1. Robustness test for substitution of dependent variables

To ensure the robustness of our findings, we employ four alternative measures of total factor productivity following the methods of Levinsohn and Petrin (2003) and Lu and Li(2012): TFP_OP, TFP_OLS, TFP_FE, and TFP_GMM. The coefficient of INT remains significantly positive at the 1% level across all these TFP measures, supporting Hypothesis 1 that higher levels of intelligent investment are associated with higher TFP.

4.4.2. PSM inspection

To address potential sample selection bias, which may affect our study's conclusions, we employed Propensity Score Matching (PSM) to mitigate the resulting endogeneity issues. The testing procedure is as follows: Median Calculation: We calculated the median of firms' intelligent investment levels. Firms above the median were coded as 1, and those below were coded as 0.Propensity Score Estimation: Using the control variables from our model, we estimated the propensity scores and matched samples at a 1:1 ratio using the nearest neighbor matching method. Regression Analysis: We conducted multiple regression analysis on the matched samples. The results, significant at the 1% level, confirm that our conclusions remain robust after addressing the endogeneity issues caused by sample selection bias.

4.4.3. Sample Re-selection

Big data technologies, broadband networks, and smart city initiatives provide enterprises with broader and faster channels for information acquisition, enabling better understanding of market demand, competitor activities, and industry trends. This enhanced information access facilitates more accurate decision-making and improves TFP. Additionally, municipalities typically invest heavily in infrastructure, including transportation, communications, and energy, which can further enhance TFP and reduce operational costs. To ensure robust results and exclude the influence of these factors, we removed samples from national big data pilots, broadband China pilots, smart city pilots, and municipalities, then reran the main effect model regressions on the remaining samples. The results confirm that our conclusions hold even after excluding these influential factors. This approach strengthens the reliability of our findings, demonstrating that the observed effects are not driven by exceptional conditions in these specific regions or programs.

5. Conclusions

This study finds that intelligent investment significantly enhances TFP, with this effect being more pronounced in state-owned enterprises and regions with more developed product markets. Mechanism analysis reveals that intelligent investment promotes TFP growth by reducing corporate financing constraints and increasing the level of intelligence within firms. The results remain robust after a series of robustness checks. This research provides empirical evidence to support the promotion of intelligent transformation and high-quality development in enterprises.

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