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AI-Driven Productivity Gains: Artificial Intelligence and Firm Productivity

Xueyuan Gao and Hua Feng *

School of Economics and Management, Beijing Jiaotong University, Beijing 100044, China; gaoxyonns@outlook.com
* Correspondence: hfeng@bjtu.edu.cn

Abstract: Artificial intelligence is profoundly influencing various facets of our lives, indicating its potential to significantly impact sustainability. Nevertheless, capturing the productivity gains stemming from artificial intelligence in macro-level data poses challenges, leading to the question of whether artificial intelligence is reminiscent of the "Solow paradox". This study employs micro-level manufacturing data to investigate the impact of artificial intelligence on firms' productivity. The study finds that every 1% increase in artificial intelligence penetration can lead to a 14.2% increase in total factor productivity. This conclusion remains robust even after conducting endogeneity analysis and a series of robustness tests. The study identifies that the positive impact of artificial intelligence on productivity is primarily achieved through the value-added enhancement effect, skill-biased enhancement effect, and technology upgrading effect. Furthermore, the study reveals that the effects of artificial intelligence on productivity vary across different property rights and industry concentration contexts. Additionally, the structure of factor endowments within firms can also influence the productivity gains from artificial intelligence. Our study presents compelling evidence demonstrating the role of artificial intelligence in fostering economic sustainability within the framework of Industry 4.0.

Keywords: artificial intelligence; productivity; total factor productivity; technological upgrading; labor force skills

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1. Introduction

Artificial intelligence (AI), a rapidly developing technology in recent years, has demonstrated immense potential and is increasingly being adopted in various domains of social activities. As its applications continue to expand, AI has the potential to significantly impact sustainability, productivity, and economic growth. In certain specialized areas, AI is already capable of performing on par with humans, such as in computer vision. Given the abundance of data at hand, it is not too far-fetched to envision AI as the next generation of general-purpose technology (GPT). Throughout history, successive GPTs have consistently brought about profound impacts on productivity and overall economic sustainability.

People generally have a positive attitude towards the sustainability opportunities provided by Industry 4.0 [1]. Sustainable development encompasses not only environmental concerns but also economic development and social resources [2]. AI, considered one of the most advanced categories of technology [3], is expected to play a key role in influencing economic sustainability. Scholars express confidence that the application of Industry 4.0 and related digital technologies will have a positive impact on sustainable development [4].

Productivity has always been a crucial indicator of an economy's potential for achieving sustainability. Economies with higher productivity are more likely to sustain long-term economic growth, while firms that exhibit greater productivity tend to have a higher survival rate compared to less-productive counterparts. From an economic standpoint, sustainability can be viewed as a sustained increase in productivity. Enhancing productivity means that a company's current production methods surpass its previous ones. Thus, continuous growth in productivity signifies the establishment of a sustainable production model, enabling the firms to achieve sustainability from an economic perspective. While we can already feel the productivity gains from AI in many ways [5,6], the macroeconomic data do not provide supporting evidence, and the productivity gains from AI seem to be a replication of the "Solow paradox" [7]. The "Solow Paradox" has prompted numerous scholars to explore the connection between information technology (IT) and sustainable economic growth. It appears that groundbreaking technologies have not consistently resulted in economic sustainability. During this period of rapid AI development, the total factor productivity (TFP) of countries around the world is declining significantly [8], which is the main reason why many scholars are pessimistic about AI. However, the reasons for this phenomenon are more often attributed to a buffer period in which the economy needs to restructure and reorganize its production patterns [9], or to observation bias due to statistical errors [10,11]. In fact, these studies suggest that AI has the potential to increase productivity and achieve economic sustainability, but the productivity effect is not manifested at the macro level because of the lag in reorganization, again suggesting that the evidence of productivity gains from AI is not currently captured at the macro level.

This raises the question of whether we can effectively capture evidence of AI's impact on productivity at the micro level if it does lead to sustainability. However, quantitative studies examining AI-induced sustainability at the micro level are very scarce [12]. Due to the lack of micro data, only a handful of studies provide preliminary evidence [13,14]. These studies primarily focus on the development of AI in developed countries, with limited research on the productivity impact of AI in developing countries.

In this paper, our objective is to present quantitative analytical evidence of the economic impact of AI on sustainability. Specifically, we investigate the effect of AI on productivity using micro-level data from Chinese manufacturing firms. China, being a developing country with a strong competitive advantage in the field of AI, offers a unique context to study the impact of AI on productivity. In 2018, Chinese companies exclusively accounted for the top five out of the top ten facial recognition algorithm companies in the world, with facial recognition being a major track in AI. Additionally, China boasts the largest number of industrial robots globally. This rapid development of AI in China provides an excellent opportunity to observe the impact of AI on sustainability, and fills the gap in the literature that lacks studies focusing on developing countries as research subjects.

We present micro-level evidence of the impact of AI on productivity. The empirical findings from baseline regression analysis reveal a significant positive effect of AI on the TFP of manufacturing firms. To address potential endogeneity concerns arising from omitted variables and reverse causality, we employ instrumental variable (IV) regressions to establish a causal relationship between AI and TFP. The results of various robustness tests further support this conclusion.

Furthermore, we investigate the potential mechanisms through which AI impacts productivity: the value-added enhancement effect, the skill-biased enhancement effect, and the technology upgrade effect. Firstly, AI enables firms to enhance their value-added products, leading to an increase in the value of output from various factor inputs and thus boosting firm productivity. Secondly, AI drives adjustments in firms' skill structures, resulting in the hiring of more high-skilled employees. This leads to the improved absorption and utilization of new technologies in developing countries, thereby enhancing firms' productivity through human-capital accumulation. Thirdly, AI facilitates technological upgrading in enterprises, stimulating innovation output in the AI field and promoting overall innovation output, which generates spillover effects. These innovations serve as determinants for enhancing TFP.

The findings of the heterogeneity analysis reveal that the nature of property rights, industry concentration, and the structure of factor endowments can result in heterogeneous effects on the productivity impacts of AI. Specifically, we observed that AI significantly enhances the productivity of non-state-owned enterprises (Non-SOEs). The productivity gains from AI are particularly pronounced in industries with a high concentration. Furthermore, we found that firms in capital-intensive and technology-intensive industries experience significant productivity improvements as a result of AI.

Our study contributes significantly to the emerging literature on AI and sustainability in several ways. First, we examine the potential impact of AI on sustainability from an economic theory perspective. While the economic dimension is recognized as an integral part of sustainability [15], there is a lack of research that applies modern economic theory to the study of sustainability. Our study initiates the exploration of AI's impact on sustainability from an economic standpoint.

Second, we provide quantitative analytical evidence regarding the impact of AI on sustainability. Existing studies predominantly offer qualitative analyses [16] and lack comprehensive assessments of the sustainability achieved through AI [17]. Few studies have systematically evaluated the contribution of AI to sustainability in the business sector, which plays a central role in realizing the UN 2030 Sustainable Development Goals. Our study offers an approach to assess the impact of AI on sustainability through an economic lens, particularly by examining AI's influence on productivity. Furthermore, our findings demonstrate that AI has a positive impact on sustainability, countering overly pessimistic views on AI technologies [18,19].

Third, we provide quantitative evidence illustrating how AI contributes to sustainability, particularly through innovation. Through our quantitative analysis, we observe that AI not only stimulates firms to generate more AI innovations (evidenced by increased AI patent filings), but also facilitates other forms of patent output. This suggests that AI can assist firms in achieving sustainability by promoting innovation activities with spillover effects.

We also have the potential to contribute to the application of the productivity concept in sustainability research. Developing sustainable production models is a crucial aspect of the business sector's sustainability goals. The viability of a production model in terms of sustainability heavily relies on the continuous growth of the productivity it generates. While a few studies have conceptually mentioned the possibility of using productivity to examine sustainability [20,21], our study goes further by utilizing TFP as a measure of productivity. TFP captures the increase in productivity levels resulting from technological advancements, making it a more suitable indicator for investigating the topic of sustainability.

The structure of this paper is as follows. In Section 2, we provide a review of the existing literature related to AI and productivity. Section 3 describes the data sources, variables, and the identification method used in this study. Section 4 presents the empirical analysis, which includes the baseline regressions, endogeneity analysis, and robustness tests. In Section 5, we delve into the mechanism analysis and heterogeneity analysis to explore the underlying channels of the relationship between AI and productivity. Finally, Section 6 provides a summary of our findings.

2. Theoretical Background

2.1. *Artificial Intelligence*

AI is not a new concept that has emerged in recent years. It was first proposed at the Dartmouth Conference in 1956. Turning [22] proposed a method to test whether machines have human intelligence, which is still the ultimate test of AI. In the Physical Symbol System Hypothesis (PSSH), Simon hypothesizes that computers can simulate humans or simulate human brain functions [23]. The direction of AI has always been focused on simulating human behavior and effectively handling various tasks, aiming to achieve a level of capability comparable to that of humans. After two troughs, AI applications are expanding and showing great commercial value in recent years, thanks to the development of deep-learning technology [24]. AI is developing at an unprecedentedly fast pace.

Economists have strived to analyze the role of AI in production activities within the realm of economic phenomena. The prevailing consensus among academics is that AI is increasingly replacing humans in a wide range of jobs. Aghion et al. [25] consider AI as a "machine's ability to mimic intelligent human behavior" that can replace the worker for many specific tasks. Makridakis [26] argues that AI as an automation tool can significantly improve productivity by complementing and replacing human labor in repetitive operations and standardizing processes. By systematically decomposing intricate tasks into numerous smaller components, AI leverages machine learning algorithms to address these specific tasks and tackle complex problems effectively [27]. Acemoglu and Restrepo [28] adopt a comprehensive perspective on AI, encompassing the research and development of intelligent agents—whether they are machines, software, or algorithms—that exhibit intelligent behavior by perceiving and responding to their environment.

The increased degree of application of AI in complex tasks means that its impact on economic activity is expanding as never before, giving AI the potential to become the next generation of GPT. A technology has the potential to become GPT if it can be used widely across a variety of sectors and dramatically change operating patterns [29]. Cockburn et al. [30] argue that AI, including robots and sensors, can be considered as a type of GPT that can generate a large number of subsequent innovations that ultimately lead to productivity growth.

2.2. AI and Productivity

The gradual integration of AI technologies into complex tasks has the potential to significantly impact productivity across a wide range of economic activities. Productivity, which measures the efficiency of transformation, has long been a focal point in economic studies. At the micro level, higher productivity signifies the ability of firms to endure and thrive, while sustained growth in overall productivity signifies economic sustainability. In light of the wealth of production data available, economists have started to dissect aggregate productivity into its various micro-level components in order to elucidate the sources of this growth [31]. Numerous scholars have examined the influence of factors such as management practices [32], labor [33], and innovation [34] on productivity. The impact of IT on productivity has been a prominent research theme. Oliner et al. [35] regard IT as a distinct form of capital and have confirmed its central role in the productivity resurgence observed in the United States from 1995 to 2000, while also noting its continued but relatively smaller impact in the post-2000 era.

When a technology is introduced into economic production, firms adjust their production processes and change their factor structure accordingly to accelerate the application of the new technology and reap its benefits. Acemoglu et al. [36] argue that the application of new technologies makes firms incur new fixed costs, which is a necessary prerequisite for firms to apply new technologies to increase productivity. To reap the full benefits of the technology, complementary investments are necessary and will take some time [9]. This is an essential reason why productivity advances from AI are not observed in macroeconomic data at the moment. TFP is declining in developed countries. Developing countries are also experiencing a similar situation [8]. The continued decline in productivity has left many scholars pessimistic about the future of AI applications [37].

It cannot be ignored that we are already experiencing significant benefits from AI, in terms of innovative R&D [38], happiness [39], green development [40], etc., which clearly contradict the macro-level research. Bonetti et al. [41] delved into the application of AI in the retail industry and ascertained that the co-evolution of practices is crucial for maximizing the effectiveness of AI in retail applications. Boyaci et al. [42] discovered that AI has the potential to enhance the overall accuracy of human decision-making, despite a potential increase in the likelihood of certain errors.

One possible explanation is that AI is already having a clear impact on productivity, but the spread is just not large enough yet. The few current studies based on micro data have found a positive impact of AI on productivity. Graetz and Michaels [13] identified that robots can significantly improve labor productivity and TFP by using industry-level data from 17 countries over the period of 1993–2007. Unlike many studies that argue that robots reduce employment [43,44], they found that robots do not reduce overall employment levels. Using the sample of manufacturing firms from the European Manufacturing Survey 2009, Jäger et al. [14] finds that the use of industrial robots significantly improves productivity and argues that the cost of investment may be one of the perceived barriers to the use of industrial robots by SMEs. While these studies consider the positive effects of AI on productivity gains, they do not analyze the mechanisms of gains in depth and use relatively old sample data.

Some scholars have explained this huge difference in performance between macro and micro from a theoretical perspective. Aghion et al. [25] provided an explanation for this phenomenon based on the task framework proposed by Acemoglu and Restrepo [45]. In their modeling, the impact of AI on GDP depends on the balance between the two forces. On the one hand, a greater proportion of goods that are automated increases the share of automated goods in GDP, which gives rise to an increase in the share of related investment and thus the importance of AI in GDP. On the other hand, when the elasticity of substitution is less than one, capital accumulation causes the price of automated goods to fall. Due to the relative inelasticity of demand, people's demand for these goods will likewise fall, which will cause the share of AI's contribution to overall GDP growth to fall. The dynamic influence of these two forces then has the potential to make the contribution of AI in the process of productivity growth tend towards zero.

The micro-foundation of these two forces is determined by the dynamic influence between AI and human capital. The impact of AI on tasks depends on the dynamic trade-off between productivity effect and displacement effect [12]. The productivity effect reflects AI's ability to impact productivity by adjusting relative factor prices. The application of AI causes the price of producing a particular task to fall, thus giving AI a comparative advantage over labor in that task, so the productivity effect is positive. At the extensive margin, the accumulation of AI capital increases the real wage from making the productivity effect stronger. At the extensive margin, the upgrade of AI technology will make the production efficiency of tasks that have been automated continuously improved, which will likewise amplify the productivity effect. Not only that, AI may also create new tasks where the workforce has a comparative advantage, further contributing to productivity gains. However, it is worth noting that AI may not necessarily have a significant impact on productivity. If the difference in production efficiency after adopting AI is not substantial compared to the previous state, then AI can be considered as a "so-so" technology.

2.3. AI, Employment and Innovation

The productivity effect means that AI has a huge impact on employment and innovation. However, studies in these areas have not reached consistent conclusions. Acemoglu and Restrepo [46] studied the impact of AI on the structure of the labor force and argue that there is a heterogeneous impact of AI on the labor force and that robots may reduce employment and wages in the local market. Kellogg et al. [47] ascertained that employers utilize algorithms to manage records and ratings, enabling them to effectively evaluate workers and recognize and incentivize high-quality employees.

Autor [48] argues that while automation can replace some of people's routine and codable tasks, people still have a comparative advantage in areas such as solving complex problems and producing ideas. However, studies in recent years have found that AI seems to perform better than humans in certain specific complex problems or innovative activities. Cockburn et al. [30] argue that AI has become "the general invention of invention methods". Rammer et al. [49] found that the share of AI in innovation activities is gradually increasing. Agrawal et al. [50] argue that AI helps researchers deal with the "burden of knowledge" as well as providing researchers with recommendations for the most appropriate knowledge. However, some scholars argue that there are certain conditions under which AI can effectively contribute to knowledge-production tasks. Lebovitz et al. [51] propose that AI's role in knowledge work is not universal, emphasizing the importance of integrating human knowledge with AI knowledge for optimal utilization. Mariani et al. [52] argue that the adoption of AI stimulates firms to generate a wide range of innovative outputs.

3. Data, Variables and Identification Method

3.1. Data

To investigate the potential positive impact of AI on productivity, we construct a database of Chinese A-share-listed manufacturing companies from 2010–2021 to analyze the impact of AI on productivity. The A-share-listed manufacturing companies are selected for the study because manufacturing is an important application area of AI. Meanwhile, China's manufacturing industry is the largest in the world and is a suitable industry to study the productivity effects generated by AI from a microscopic perspective. These companies are representative, and most of them are continuously surviving during the period of our selected sample, which facilitates us to observe the impact of AI on firm productivity over a relatively long period of time and increases the credibility of our study.

Our data were mainly obtained from the following databases: firm-level data is mainly from the China Stock Market & Accounting Research Database (CSMAR) and related annual reports, and patent data are from the China National Intellectual Property Administration (CNIPA). We pre-processed the data, removed the samples of ST and PT cases, and also removed the samples of firms with seriously missing relevant variables, and finally obtained a sample of 20,904 observations from 2899 manufacturing listed companies. On this basis, we applied a 1% tail reduction to all continuous variables. All regressions were clustered at the firm level.

3.2. Variables

3.2.1. Independent Variable

Some recent studies have used industrial robotics data from the International Federation of Robotics (IFR) as a core indicator of AI development, but the IFR data are primarily industry-focused and lack detailed information on AI adoption by firms. This measurement approach considers robots as an aggregate of various types of AI technologies, which has some validity, but it weakens the rapid growth of AI in recent years due to advances in deep learning and machine learning, which is precisely one of the important reasons why AI is considered a next-generation GPT that can iterate itself and has a strong productivity-enhancing effect. Therefore, we tried to capture the application of AI technologies at the firm level using a natural language processing (NLP) approach.

The benefit of using the NLP approach is that it captures the enterprise's application of AI technology in a timely manner. Many AI capitals are difficult to measure, and while the value generated by AI may be intangible and embedded within a final product, using NLP can help one observe AI trends. Carbonero et al. [53] used this method to study and analyze the impact of AI on the labor market. Using annual report data from listed manufacturing companies, we constructed a composite metric that included both the basic and application layers to measure the AI penetration of firms. The basic layer covers the application of the algorithm and technology level, while the application layer mainly covers the application scenarios of AI in the manufacturing industry, highlighting the application of AI in production activities; see Table A1 Appendix A for details. After we obtained the relevant word-frequency information, we divided it by the length of the Management's Discussion and Analysis (MD&A) section of the annual report. The calculation method of this indicator is shown in Equation (1), where Len (MD&A) represents the length of the MD&A paragraph, and $\mathrm{AI_{basic}}$ and $\mathrm{AI_{application}}$ represent the word frequencies in the basic layer and the application layer, respectively. This is a positive indicator, where a higher value indicates a greater level of AI penetration in the firm.

$$\mathrm{AI_{density}} = \frac{\mathrm{AI_{basic}} + \mathrm{AI_{application}}}{\mathrm{Len(MD\&A)}} \quad (1)$$

3.2.2. Dependent Variable

We used TFP to measure the productivity of a firm. TFP measures the total output of all input factors in an economy in a given period and is a common measure of productivity.

When the total factor input/output in the current period exceeds that of the previous period, it indicates a growth in productivity levels. Referring to the LP method [54], the firm-level TFP is calculated using the Cobb–Douglas function (C–D production function), as shown in Equation (2).

$$\ln Y_{it} = \beta_0 + \beta_k \ln K_{it} + \beta_l \ln L_{it} + \beta_m \ln M_{it} + \beta_I \ln I_{it} + \omega_{it} + \varepsilon_{it} \quad (2)$$

In Equation (2), Y_{it} is the total output of firm i in year t, measured using the firm's operating income. K_{it} is the capital investment of firm i in year t, measured using the firm's net investment in fixed assets. L_{it} is the labor force of firm i in year t, measured by the number of employees of the input using the firm. M_{it} is the intermediate goods input of firm i in year t, and I_{it} is the investment of firm i in year t. ω_{it} is the TFP we need. Table 1 reports the descriptive statistics of the main variables. Panel A presents the results of the descriptive analysis of the core variables, and Panel B presents the variables related to firm characteristics.

Table 1. Descriptive analysis.

Variables	(1) N	(2) Mean	(3) sd	(4) Min	(5) Max
Panel A: core variables					
TFP_LP	20,904	8.216	0.981	5.354	11.07
$AI_{density}$	20,805	0.109	0.184	0	1.178
Panel B: other variables					
TFP_OP	20,904	6.537	0.799	4.077	8.985
$AI_{density-base}$	20,805	0.00457	0.0168	0	0.133
$AI_{density-app}$	20,805	0.103	0.173	0	1.124
ROA	20,904	0.0340	0.0766	−0.400	0.200
AssetLR	20,904	0.413	0.209	0.0593	1.143
MB	20,904	0.564	0.250	0	1.139
NAVPS	20,904	4.935	3.257	−0.344	17.82
EPS	20,904	0.366	0.644	−1.826	2.850
TotalAssets	20,904	85.93	203.9	2.237	1928
Software	20,901	0.336	0.388	0	1.573
Ln (Main-income)	29,904	21.332	1.423	9.044	27.488
Ln (Value_add)	17,375	21.010	1.529	9.044	27.490
Ln (Labor)	20,550	7.680	1.177	1.099	12.570
Ln (High-skill worker)	12,942	6.016	1.247	1.963	10.900
Ln (Production)	19,119	6.992	1.357	0	12.290
Ln (Technology)	19,391	5.781	1.235	0	10.870
Ln (AI_innovation)	4469	1.264	1.344	0	7.208
Ln (Total_patent)	18,793	3.004	1.485	0	9.443
Ln (Total_invention)	14,871	1.590	1.309	0	8.038

Table 1 shows the descriptive analysis of the main variables from 2010 to 2021. Panel A shows the results for the core variables and Panel B shows the results for the other variables.

3.3. Identification Method

In the process of studying the impact of AI on productivity, there may be other factors that affect firm productivity. Factors such as industrial environment, firm operating environment, and differences in firm characteristics need to be taken into account. We referred to Acemoglu and Restrepo [46] and constructed a two-way fixed-effects model as shown in Equation (3):

$$TFP_{it} = \beta_0 + \beta_1 AI_{it} + \beta_2 X_{it} + \mu_i + \lambda_t + \mu_{ind} + \epsilon_{it} \quad (3)$$

where TFP_{it} is the total factor productivity of firm i in year t, calculated by the LP method. AI_{it} is the AI penetration of firm i in year t. X_{it} is a series of control variables that respond to firm characteristics, including the return on assets (*ROA*), book-to-market ratio (*MB*), gearing ratio (*AssetLR*), net asset value per share (*NAVPS*), total assets (*TotalAsset*), and earnings per share (*EPS*). In addition, we controled for sub-sector-fixed effects (μ_{ind}) to capture differences between sectors, firm-fixed effects (μ_i) to capture characteristics that do not change over time, and year-fixed effects (λ_t) to capture possible macro shocks. We used STATA 16.0 software for regression analysis.

The parameter β_1 in the regression equation is the coefficient we were most interested in, which measures the productivity enhancement effect due to AI. We expected the coefficient to be positive because the increase in AI penetration will accelerate the accumulation and deepening of related capital, which will greatly improve the productivity of the firm. This makes the output generated by the input in period t higher than the output generated by the input in period $t - 1$, which will increase TFP. This coefficient can also be negative if, during AI adoption, firms experience a mismatch between new technology and workforce skills, or excessive technology substitution, which can reduce productivity gains from AI or even hinder productivity gains. Therefore, β_1 helped us to examine the exact impact of AI on productivity.

4. Empirical Results

4.1. Baseline Result

In this section we examine the impact of AI on productivity using a baseline model. Table 2 shows the results of the baseline regression. The independent variable $AI_{density}$ is the firm's AI penetration, and column (1) is a regression that does not include any control variables but controls for various types of fixed effects. Column (2) presents the regression results with all firm-level control variables included. From Table 2, we can find that in column (1), the coefficient of $AI_{density}$ is significantly positive, which means that AI can indeed improve the productivity of firms. In column (2), the coefficient of $AI_{density}$ is 0.142 and is significant at the 1% level of significance. All else being equal, every 1% increase in AI penetration leads to a 14.2% increase in firm productivity. Overall, the results of the baseline regression support the hypothesis that AI in manufacturing firms significantly improves productivity.

4.2. IV Estimates for the Impact of AI

The results of the baseline regression suggest that AI significantly improves the productivity of manufacturing firms, but this finding is likely to be influenced by endogeneity issues. In fact, a manufacturing firm's decision to choose to use AI can be influenced by many factors (such as corporate culture), and even if we choose to control for some of these variables, we cannot completely rule out the possibility. Not only that, this study may also face a mutual causality, as firms with higher productivity may have higher technology needs and apply more AI for production. We tried to determine the causal relationship between AI and firm productivity using IV estimation. Specifically, we used software business revenue by region as an exogenous shock to see the impact of AI on productivity.

Many AI-related products exist in the form of intangible assets, one important manifestation of which is various types of software. The amount of revenue from a region's software business can be used to measure the potential use of AI in that region. A region with high software business revenue means that companies in the region have a better base for using AI, and companies have a greater propensity to use related technologies such as AI. At the same time, manufacturing firms do not constitute a direct link with the software business in a region; software production firms and manufacturing firms belong to different sectors and have different business scopes.

We ran a two-stage least-squares regression (2SLS), with software business revenue as the IV. Table 3 shows the regression results of 2SLS. In column (1), the coefficient of the software is significantly positive and significant at the 1% level, which is consistent with our prediction that software business revenue in the region is positively related to the penetration of AI. The Kleibergen–Paap rk LM statistic is 17.335, which is significant at the

1% level of significance. This indicates that the regression passed the under-identification test. The Cragg–Donald Wald F statistic is 23.299, which is greater than the 10% threshold (16.38), indicating the absence of a weak IV. Column (2) presents the results of the second-stage regression, where the coefficient of $AI_{density}$ is positive at the 5% significance level, implying that AI significantly improves firm productivity, which is similar to our baseline regressions in Table 2.

Table 2. The effect of AI on productivity: baseline results.

Variables	**(1)** **TFP_LP**	**(2)** **TFP_LP**
$AI_{density}$	0.221 ***	0.142 ***
	(0.049)	(0.043)
ROA		1.765 ***
		(0.167)
AssetLR		0.761 ***
		(0.069)
MB		0.222 ***
		(0.032)
NAVPS		0.031 ***
		(0.004)
TotalAsset		0.001 ***
		(0.001)
EPS		0.064 ***
		(0.021)
Constant	8.447 ***	7.814 ***
	(0.310)	(0.271)
Observations	20,805	20,805
R-squared	0.243	0.388
Number of firms	2895	2895
Sub-sector FE	Y	Y
Firm FE	Y	Y
Year FE	Y	Y

Note: Table 2 shows the regression results using the baseline model. $AI_{density}$ is the firm-level AI penetration. Column (1) is a regression controlling only for various types of fixed effects, while column (2) shows the results with the inclusion of all control variables. All regressions are clustered at the firm level. Robust standard errors in parentheses. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 3. The effects of AI on productivity: IV estimates.

	(1) **First Stage**	**(2)** **Second Stage**
VARIABLES	$AI_{density}$	TFP_LP
Software	0.020 ***	
	(0.005)	
$AI_{density}$		1.855 **
		(0.914)
Controls	Y	Y
Observations	20,445	20,445
R-squared		0.246
Number of firms	2535	2535
Sub-sector FE	Y	Y
Firm FE	Y	Y
Year FE	Y	Y
KP-F statistic		17.335 ***
CD-F statistic		23.299
		[16.38]

Note: Table 3 reports the effects of AI on productivity with IV estimates. Software is the IV. Column (1) presents the results of the first-stage regression, while Column (2) presents the results of the second-stage regression. All regressions are clustered at the firm level. Abbreviations: KP-F statistic, Kleibergen–Paap rk LM statistic; CD-F statistic: Cragg–Donald Wald F statistic. Robust standard errors in parentheses. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

4.3. Robustness Checks

4.3.1. Measuring TFP Using the OP Method

In the previous sections, we identified that AI has a positive impact on productivity enhancement in manufacturing firms and determined this causal relationship through IV regressions. However, there is also the possibility of measurement errors that can bias the estimation results. Therefore, we recalculated the firm's TFP using the OP method [55] as an alternative to the LP method. Column (1) in Table 4 presents the regression results using the OP method to measure TFP. We found that AI has a significant enhancement effect on firm productivity (1% significance level), which is in line with the direction predicted by the baseline regression results.

Table 4. Robustness checks.

VARIABLES	(1) TFP_OP	(2) TFP_LP	(3) TFP_LP	(4) TF_LP
Panel A: Measuring TFP using the OP method				
$AI_{density}$	0.067 * (0.035)			
Panel B: Impact of base layer and application layer				
$AI_{density-base}$		1.657 *** (0.364)		
$AI_{density-app}$			0.114 ** (0.046)	
Panel C: Retain sample of high disclosure credibility				
$AI_{density}$				0.140 *** (0.051)
Controls	Y	Y	Y	Y
Observations	20,805	20,805	20,805	13,510
R-squared	0.379	0.389	0.387	0.487
Number of firms	2895	2895	2895	2534
Sub-sector FE	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y

Note: Table 4 shows a series of robustness tests based on baseline regressions. All regressions include control variables and are clustered at the firm level. Robust standard errors in parentheses. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

4.3.2. Impact of Base Layer and Application Layer

Another case that may affect the accuracy of the estimation results is that the breakdown of the measure of AI penetration may have the opposite effect on productivity. Our metrics for measuring AI penetration are measured at both the base and application levels, and it is possible that an indicator at one level is detrimental to productivity improvement, while another level has an overall positive impact on productivity improvement that outweighs this negative impact. We further broke down the indicator into two layers, the base layer and the application layer, and examined their impact on firm productivity separately. Columns (2) and (3) in Table 4 report the regression results after decomposition of the indicators. We found that AI contributes to firm productivity enhancements at both the base and application layers, similar to our baseline regression results.

4.3.3. Quality of Information Disclosure

There was also a concern that our regression results may have been influenced by the quality of corporate disclosures. The indicator we used to measure AI penetration can be seriously mismeasured if the quality of the information disclosed in a company's annual report is too poor. To exclude this possible bias, we obtained the disclosure assessment ratings of each listed company and retained the sample of companies with excellent and good disclosure assessment ratings, and re-ran the baseline regression. The regression results presented in column (4) of Table 4 do not differ significantly from the baseline regression results in Table 2.

5. Mechanism and Heterogeneous Tests

5.1. Understanding the Productivity Effect of AI

In the previous section, we identified the causal relationship between AI and productivity enhancement in manufacturing firms and, to the greatest extent possible, excluded some biases that affect the accuracy of the regression results. In this section, we further explore the mechanisms by which AI affects manufacturing productivity: the value-added enhancement effect, the skill-biased enhancement effect, and the technology upgrading effect, to deepen the understanding of AI for productivity growth.

5.1.1. Value-Added Enhancement Effect

The application of AI can help firms optimize their production processes and improve inefficient production processes. AI not only reduces production costs, but also increases the firm's ability to produce more value-added products, which can increase the scale of production and increase productivity. To explore this possible mechanism, we used the firm's main business income (Main_income) and product value added (Value_added) to reflect the size of the firm's production and its ability to produce value-added products. Specifically, revenue from the main business reflects a company's basic production capacity, and for manufacturing companies, it refers to the revenue from the sale of industrial products. Value-added products reflects the value of the firm's output using various factors of production. It reflects the difference between product sales (the sum of sales of various subdivisions of industrial products) minus the cost of various intermediate goods and raw materials. Table 5 reports the baseline results for the effect of AI on product value added, and all dependent variables are logged.

Table 5. Value-added enhancement effect.

	(1)	**(2)**	**(3)**	**(4)**
	OLS		**2SLS (Second Stage)**	
Variables	**Main_Income**	**Value_Added**	**Main_Income**	**Value_Added**
$AI_{density}$	0.199 ***	0.183 ***	3.280 ***	2.931 **
	(0.055)	(0.069)	(1.261)	(1.280)
Controls	Y	Y	Y	Y
Observations	20,805	17,337	20,445	17,166
R-squared	0.447	0.338	0.188	0.185
Number of firms	2895	2513	2535	2342
Sub-sector FE	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
KP-F statistic			17.335 ***	19.405 ***
CD-F statistic			23.299	33.310
			[16.38]	[16.38]

Note: Table 5 reports the results of the test for the value-added enhancement mechanism. The dependent variables are the logarithm of the firm's main business revenue and the logarithm of the product value added, respectively. Columns (1) and (2) present the regression results for OLS. Columns (3) and (4) present the regression results for 2SLS estimation. All regressions incorporated the control variables from the baseline regression and clustered at the firm level. Abbreviations: KP-F statistic, Kleibergen–Paap rk LM statistic; CD-F statistic: Cragg–Donald Wald F statistic. Robust standard errors in parentheses. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 5 reports the effect of AI on the value added to the firm's products. Column (1) presents the results of the dependent variable being the firm's main business income; the coefficient of $AI_{density}$ is 0.199 and significant at the 1% level. Column (2) presents the results of the dependent variable being the firm value added; the coefficient of $AI_{density}$ is

0.183 and significant at the 1% level. The significant positive effects in columns (1) and (2) imply that AI not only increases the main business income of manufacturing firms, but also enhances the added value of their products. To ensure the accuracy of the mechanism analysis, we validated the mechanism using the method of IV regression, and columns (3) and (4) report these results of. We find that the coefficients of AI do not change significantly either positively or negatively, which remains consistent with the OLS results. Considering the above, we determined that AI has a significant value-added enhancement effect.

5.1.2. Skill-Biased Enhancement Effect

The use of AI in manufacturing firms will likewise expand the demand for labor in firms. AI is an advanced technology and firms need to make complementary investments in such technology to fully leverage its value, and high-skilled workers is an important complementary investment. AI replaces many of the jobs of low-skilled workers, allowing workers to focus on tasks where they have a more comparative advantage [12], which will likewise stimulate the demand for high-skilled workers by firms. In developing countries, the accumulation of human capital has a very important link with the improvement in firm productivity. Human capital, as an important carrier of knowledge and technological progress, can help firms to better absorb advanced foreign technology and continuously improve their TFP [56]. Based on these analyses, we believe that AI may have a skill-biased productivity-enhancing effect.

To test this effect, we examined whether AI produces skill-biased productivity advances in both the structure of labor demand as well as the structure of labor skills. We observed changes in the structure of labor demand in terms of both overall labor demand and the demand for high-skilled workers, as measured by the overall workforce of firms and the number of employees with college and higher-education levels, respectively. In terms of the skill structure of the workers, we used the number of production workers to measure general workers and the number of skilled workers to measure skilled workers. In manufacturing companies, production workers represent workers in the production chain with lower skill levels. Skilled workers represent workers who are engaged in professional and technical management and have higher professional skills. Table 6 report the skill-biased enhancement effect of AI. In Table A3 Appendix B, we also report the results of the IV regression.

Table 6. Skill-biased enhancement effect.

Variables	**(1)** **ln(Labor)**	**(2)** **ln(High-Skill Worker)**	**(3)** **ln(Production)**	**(4)** **ln(Technology)**
$AI_{density}$	0.227 ***	0.170 ***	0.269 ***	0.378 ***
	(0.055)	(0.060)	(0.068)	(0.070)
Controls	Y	Y	Y	Y
Observations	20,453	12,878	19,036	19,307
R-squared	0.243	0.371	0.174	0.228
Number of firms	2843	2205	2790	2814
Sub-sector FE	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y

Note: Table 6 reports the results of the test for the skill-biased enhancement effect. All results were obtained by regression on the basis of the baseline model. Columns (1) and (2) present the impact of AI on the structure of labor demand, and Columns (3) and (4) present the impact of AI on the structure of labor skills. All regressions include control variables and are clustered at the firm level. Robust standard errors in parentheses. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

The regression results from Table 6 indicate that AI has a significant positive effect on the structural shift in labor demand and the upgrading of labor skills. Columns (1) and (2) present the impact of AI on the structure of labor demand. We find that AI increases firms' demand for overall labor while also increasing the demand for high-skilled workers. When AI penetration increases by 1%, firms' demand for total workers and highly skilled workers increases by 22.7% and 17%, respectively. Columns (3) and (4) report the effect of AI on the skill structure of the labor force. Similar to the change in the structure of labor demand, AI significantly increases firms' demand for specialized skilled workers, and this enhancement effect is much larger than that of production workers (0.378 > 0.269). These results suggest that AI does produce a skill-biased enhancement effect.

5.1.3. Technology Upgrading Effect

AI has the potential to have a technology upgrading effect. On the one hand, in developing countries, the introduction of AI in manufacturing firms requires complementary investments to update production lines. Firms accumulate relevant technological experience in the process of upgrading current production lines, which stimulates complementary innovation and generates significant knowledge spillover. On the other hand, when firms benefit from the production advantages brought by AI, manufacturing firms will enhance the exploration of AI-specific innovations in order to achieve further productivity development, which strengthens the R&D of AI-specific technologies. Therefore, the application of AI may not only stimulate innovation related to itself, but also may have a spillover effect to stimulate more additional innovative activities by firms. Innovation activities will play a decisive role in firm productivity, especially TFP [57,58], so we believe that AI may have a technological upgrading effect.

To verify this possible mechanism, we studied the impact of innovation generated by AI in two ways: the total innovation activity of the firm and the innovation performed by the firm in terms of AI. Specifically, we used the logarithm of all patents (ln(Total patent)) and the logarithm of invention patents (ln(Invention patent)) to describe the overall situation of firms' innovation activities. When firms are more innovative, they will have a stronger incentive to apply for patent protection and obtain innovation rents. In China, invention patents are often considered to be the highest-value patents, which can effectively reflect the quality of corporate innovation. We also tried to observe AI-specific innovation by manufacturing firms, where the use of AI may prompt firms to construct technological barriers based on the AI technology itself. To determine this impact, we measured innovation in this category using AI-related patents. Part of the literature mainly includes the category G06N in the IPC [59], on which we have appropriately expanded to adapt AI innovations in manufacturing, mainly including the subcategories G06N, G06F, G05B, etc., which are detailed in Table A4. Table 7 reports the regression results under the baseline regression model. In Table A5, we also report the results of the IV regression.

Table 7. Technological innovation effect.

VARIABLES	(1) ln(Total Patent)	(2) ln(Invention Patent)	(3) ln(AI-Specific)	(4) TFP_LP
$AI_{density}$	0.303 ***	0.305 ***	0.311 **	0.032 ***
	(0.092)	(0.088)	(0.145)	(0.012)
AI-specific				0.134 ***
				(0.042)
Controls	Y	Y	Y	Y
Observations	18,702	14,796	4444	4469
R-squared	0.316	0.186	0.258	0.438
Number of firms	2824	2627	1284	1289
Sub-sector FE	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y

Note: Table 7 reports the results of the test for the technological innovation effect. AI innovation represents patents related to AI. All results were obtained by regression on the basis of the baseline model. All regressions incorporate the control variables from the baseline regression and cluster at the firm level. Robust standard errors in parentheses. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

From the regression results of Table 7, we can find that AI plays a significant positive role in promoting the innovation ability of enterprises. Columns (1) and (2) present the overall impact of AI on firms' innovation activities. The coefficient of $AI_{density}$ is significantly positive (at 1% significance level), implying that AI significantly increases the quantity and quality of firms' innovation activities. Column (3) presents the results for AI-specific innovations; the coefficient of $AI_{density}$ is also significantly positive, and when AI penetration increases by 1%, the firm's patents in the direction of AI will increase by 31.1%. This indicates that the application of AI stimulates firms to make AI innovations. One might be concerned that our variable measuring AI innovation might absorb the effect of the independent variable. Therefore, in Column (4), we include both together in the baseline regression. Both the coefficient of $AI_{density}$ and the coefficient of AI-specific innovation are significant, thus ruling out this possible effect. In conclusion, through the above analysis, we determined that AI produces a technological innovation effect.

5.2. The Heterogeneous Effects of AI

In this section we focus on the effects of heterogeneity in the nature of property rights, industry concentration, and the factor endowment structure of AI. Detailed results are presented in Tables 8 and 9.

Table 8. Heterogeneous impact of AI (nature of property rights and industry concentration).

Heterogeneous Group Variables	**(1) SOEs TFP_LP**	**(2) Non-SOEs TFP_LP**	**(3) High Concentration TFP_LP**	**(4) Low Concentration TFP_LP**
$AI_{density}$	−0.059	0.186 ***	0.150 ***	0.126 **
	(0.078)	(0.049)	(0.054)	(0.055)
Controls	Y	Y	Y	Y
Observations	5358	15,447	10,457	10,348
R-squared	0.453	0.381	0.402	0.389
Number of firms	690	2495	2653	2616
Sub-sector FE	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y

Note: Table 8 reports the impact of heterogeneity in AI (nature of ownership and industry concentration). All results were obtained by regression on the basis of the baseline model. All regressions incorporate the control variables from the baseline regression and cluster at the firm level. Robust standard errors in parentheses. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 9. Heterogeneous impact of AI across industries.

Variables	**(1) Labor-Intensive TFP_LP**	**(2) Capital-Intensive TFP_LP**	**(3) Technology-Intensive TFP_LP**
$AI_{density}$	0.138	0.140 *	0.106 **
	(0.117)	(0.078)	(0.051)
Controls	Y	Y	Y
Observations	4750	5126	10,893
R-squared	0.349	0.379	0.397
Number of firms	672	741	1648
Sub-sector FE	Y	Y	Y
Firm FE	Y	Y	Y
Year FE	Y	Y	Y

Note: Table 9 reports the impact of heterogeneity in AI across industries. All results were obtained by regression on the basis of the baseline model. All regressions incorporate the control variables from the baseline regression and cluster at the firm level. Robust standard errors in parentheses. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

5.2.1. Heterogeneity in the Nature of Property Rights

Differences in the nature of firms' property rights may have heterogeneous effects on AI-induced productivity effects. We examined the impact of AI by dividing firms into state-owned enterprises (SOEs) and non-SOEs. SOEs have more administrative tasks than non-SOEs and are important for maintaining social stability [60]. In this case, SOEs may be more prone to resource misallocation as well as incentive distortions, when AI may not produce significant productivity gains. Table 8 reports the results of the baseline regressions.

Columns (1) and (2) in Table 8 present the results of the baseline regressions in the SOE subsample and the non-SOE subsample, respectively. For non-SOEs, AI significantly improves productivity, with an 18.6% increase in productivity when AI penetration increases by 1%. However, for SOEs, AI does not bring significant productivity gains or may even bring losses. The results of Columns (1) and (2) suggest that market-oriented reforms of SOEs should be accelerated to reduce the degree of resource mismatch in SOEs in order to effectively release the productivity effects brought by AI.

5.2.2. Degree of Industry Concentration

Differences in industry concentration may likewise have heterogeneous effects on AI-induced productivity effects. We tested the effect of AI on productivity by dividing the sample into two groups, high industry concentration and low industry concentration, respectively. In more concentrated industries, a few large firms capture the majority of the market share, allowing AI to be deployed at scale, generating economies of scale and increasing productivity. In contrast, within less-concentrated industries, the scale at which firms can deploy AI is relatively small, and the productivity-enhancing effects of AI may be relatively small. Large firms with scale advantages benefit more from technological advances [61]. We grouped the sample into high and low industry concentration subgroups according to the median industry concentration. Table 8 reports the results of the regressions.

Columns (3) and (4) of Table 8 report the results of the baseline regressions for the subsamples in the high- and low-concentration industries, respectively. AI significantly increases the productivity of firms in the different subgroups. In Column (3), for every 1% increase in AI penetration, there is a 15% increase in firm productivity, when all else is held constant. In Column (4), this effect is 12.6%. Firms in highly concentrated industries have significantly higher productivity gains than those in less-concentrated industries. This implies that the productivity gains from AI are likely to be scale-biased, benefiting large-scale firms more.

5.2.3. Heterogeneous Effects of Factor Endowment Structure

Differences in the structure of factor endowments may likewise have heterogeneous effects on AI-induced productivity effects. We classified industries into three groups: labor-intensive, capital-intensive, and technology-intensive, and examined the impact of AI on the productivity of firms within different industries, respectively. The detailed classification method is shown in Table A6. Technological progress is often non-neutral. Not only does the factor endowment of each industry differ significantly, but the specific scenarios in which AI can be applied are also markedly different. Due to differences in the structure of resource endowments, the benefits that firms derive from new technologies can likewise vary significantly [62].

In technology-intensive industries, firms may be more inclined to use AI to solve specific technical problems and help iterate and upgrade existing technologies. In capital-intensive industries, firms use AI mainly for production applications, preferring to replace labor and automate production. In labor-intensive industries, AI technologies may have great difficulty changing the factor endowment structure of firms themselves, and even if they replace labor, they may be "so-so" technologies [12]. These technologies are only slightly better than labor and do not produce significant productivity advances. Therefore, we predicted that the productivity effect of AI would be more pronounced in capital-intensive and technology-intensive firms, while it was likely to be insignificant or even negative in labor-intensive firms.

Table 9 presents the regression results on the differences in factor endowments. Column (1) presents heterogeneous effects in labor-intensive industries, indicating that AI does not significantly enhance the productivity of labor-intensive firms. Columns (2) and (3) present the heterogeneous impact in capital-intensive and technology-intensive industries, respectively. Other things being equal, when the penetration of AI increases by 1%, the productivity of firms in capital-intensive and technology-intensive industries increases by 14% and 10.6%, respectively.

6. Conclusions

With the rapid development of AI technology, its increasing penetration across various sectors of the economy is inevitable. AI is not only automating simple tasks but also becoming involved in complex tasks, which can have profound impacts on productivity and sustainability. Our study provides evidence on the productivity effects of AI from a microscopic perspective, identifying a causal relationship between AI and TFP in manufacturing firms. Specifically, we found that a 1% increase in AI penetration leads to a significant 14.2% increase in firm TFP. We illustrated the significant positive impact of AI on sustainability, particularly from a productivity standpoint. While the benefits of AI on productivity may not be immediately evident in macro-level data, we firmly believe that over a longer adjustment period, the crucial value of AI in enhancing productivity and promoting sustainability will become apparent.

We quantified the impact of AI on sustainability, specifically focusing on its effect on productivity. Based on firm-level data from China's manufacturing industry, our study found that AI has a significant positive impact on firms' TFP through multiple channels, including the value-added enhancement effect, skill-biased upgrading effect, and technology upgrade effect. AI enables firms to improve their productivity, leading to increased main business income and higher added value of products. This results in higher output from all factors of production in the current period compared to the previous period, leading to a significant increase in TFP. Furthermore, the adoption of AI has also stimulated firms to increase their demand for highly skilled workers and specialized technical workers. In developing countries, a skilled workforce is a crucial form of human capital that enables firms to absorb advanced technologies, thereby further enhancing TFP. Additionally, our research indicates that AI has a significant technology spillover effect. The application of AI not only promotes technology exploration in the AI field itself but also stimulates overall innovation activities of firms, leading to further increases in TFP. To the best of our knowledge, the little research provides a detailed mechanistic analysis of the productivity impact arising from AI. Our mechanistic analysis provides an important analytical channel for understanding the impact of AI on sustainability.

Our study also identifies heterogeneity in the effects of AI on productivity based on the nature of property rights, industry concentration, and factor endowment structure. AI has significant productivity effects on TFP in non-SOEs, while the effects are not significant in SOEs due to resource misallocation and incentive distortion caused by multi-tasking. A high industry concentration facilitates firms in deploying AI at scale, leading to significant productivity gains from scale effects. Furthermore, we find that AI increases firm productivity in both capital-intensive and technology-intensive industries. Our analysis further provides additional suitable environments for deploying AI applications and enriches the research on application scenarios.

These findings have positive implications for understanding the impact of AI on sustainability. These findings can provide valuable insights for company leaders to adopt targeted interventions and establish sustainable production patterns, thereby facilitating the achievement of sustainability goals within their organizations. Policymakers can use our findings as a guide to amplify the productivity effects of AI by subsidizing AI investment and R&D, as well as improving workforce skill levels. Differentiated AI subsidy policies based on industry and market characteristics may also be necessary.

Our study has some limitations that warrant further investigation. The study is limited to the manufacturing sector due to data availability, and the impact of AI on sustainability in other industries may vary. Additionally, within-firm-level data are lacking, which could provide insights into the relationship between AI and specific tasks, and further investigation with access to such data could provide a more direct micro-level perspective on the impact of AI on sustainability.

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Appendix A

Table A1. Construction method of AI penetration.

$AI_{density}$	Keywords
Base layer	Artificial intelligence, image recognition, intelligent data analysis, machine learning, deep learning, semantic search, speech recognition, face recognition, natural language processing, identity recognition.
Application Layer	Intelligent robot, business intelligence, autonomous driving, industrial internet, intelligent energy, intelligent wear, intelligent transportation, intelligent medical, intelligent agriculture, intelligent home, intelligent environmental protection, intelligent power grid, industrial intelligence, intelligent factory, automatic monitoring, automatic detection, intelligent manufacturing, intelligent, CNC, intelligent fault diagnosis, industrial internet, automatic control, automatic detection, automatic production, integration, memory computing

Table A2. Specific description of the main variables.

Variables	Description
TFP_LP	TFP calculated using the LP method
TFP_OP	TFP calculated using the OP method
$AI_{density}$	For details, please refer to the calculation method in the text
ROA	Net Income/Average Balance of Total Assets
AssetLR	Total liabilities divided by total assets at the end of the year
MB	Book value/total market value
NAVPS	Ratio of the company's net income to outstanding common shares
EPS	Ratio of profit after tax to total equity
TotalAssets	Total assets by item
Software	Regional software business revenue
ln(Main-income)	Log term of revenue from main business
ln(value_add)	Log term of added value
ln(labor)	Log term of the total labor force
ln(High-skill worker)	Log term of high-skill labor force
ln(Production)	Log term of production employees
ln(Technology)	Log term of technical staff
ln(AI_innovation)	Log term of AI patents
ln(Total_patent)	Log term of total patents
ln(Total_invention)	Log term of invention patents

Appendix B

Table A3. Skill-biased enhancement effect (2SLS estimation).

Variables	(1) ln(labor)	(2) ln(High-Skill)	(3) ln(Production)	(4) ln(Technology)
$AI_{density}$	4.125 ***	2.796 *	1.538 *	3.761 ***
	(1.318)	(1.359)	(0.928)	(1.194)
Controls	Y	Y	Y	Y
Observations	20,098	12,472	18,682	18,949
Number of firms	2488	1799	2436	2456
Controls	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
KP-F statistic	16.658	12.756 ***	24.760 ***	22.578 ***
CD-F statistic	22.327	16.745	33.444	30.500
	[16.38]	[16.38]	[16.38]	[16.38]

Note: Table presents the IV estimation of skill-biased enhancement effect. Abbreviations: KP-F statistic, Kleibergen–Paap rk LM statistic; CD-F statistic: Cragg–Donald Wald F statistic. Robust standard errors in parentheses. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A4. AI-specific innovation IPC code.

IPC	Main Content
G06N	Mainly includes computational methods and systems for artificial intelligence, including machine learning, neural networks and fuzzy logic.
G06F	Computer system architecture, hardware, software and computing methods, including computer networks, database management, algorithms.
G06Q	Computing methods or systems for business or management, including e-commerce, financial technology, and marketing.
G06T	Computer graphics, image processing, pattern recognition and computer vision.
G05B	Methods or systems for controlling or regulating robots.
B23Q	Tool machines such as lathes, drilling machines, milling machines, etc., can be used to refer to robot-related processing equipment or integrated applications of robots.
B25J	Robotics, including robot structure, control system, sensors, etc.
H01L	Semiconductor device or manufacturing technology, which can also be used to describe semiconductor technology related to robotics.
H04N	Video communications, including video processing and transmission technologies.

Table A5. Technological innovation effect (2SLS estimation).

Variables	(1) ln(Total Patent)	(2) ln(Invention Patent)	(3) ln(AI Innovation)
$AI_{density}$	3.246 *	3.339 *	2.324 **
	(1.824)	(2.020)	(1.092)
Controls	Y	Y	Y
Observations	18,330	14,353	3254
R-squared	0.216	0.037	0.173
Number of firms	2452	2184	706
Sub-sector FE	Y	Y	Y
Firm FE	Y	Y	Y
Year FE	Y	Y	Y
KP-F statistic	17.207 ***	12.856 ***	14.091 ***
CD-F statistic	22.791	16.725	43.395
	[16.38]	[16.38]	[16.38]

Note: Table A5 presents the IV estimation of technological innovation effect. Abbreviations: KP-F statistic, Kleibergen–Paap rk LM statistic; CD-F statistic: Cragg–Donald Wald F statistic. Robust standard errors in parentheses. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A6. Factor endowment structure of each industry.

Factor Endowment Structure	Industry Code
Labor-intensive	C12 C13 C14 C15 C16 C17 C18 C19 C20 C21 C22 C23 C24 C32 C34
Capital-intensive	C25 C26 C28 C29 C30 C31 C33
Technology-intensive	C27 C35 C36 C37 C38C39 C40 C41

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