An Emprical Evidence: Research on the Relationship Between Artificial Intelligence and Productivity Convergence

Jiamin Yu[a,*] & Yan Sen[b]

[a]School of Humanities and Social Sciences, Macao Polytechnic University, Macao, China
[b]School of Economic and Management, Southeast University, Jiangsu, China

*p2209639@mpu.edu.mo, 230218852@seu.edu.cn

Abstract. The development of artificial intelligence (AI) presents unprecedented opportunities for comprehensive economic growth and productivity improvement. This paper reviews recent development trends of AI and the factors influencing productivity convergence. We focused on the current state of research on AI's impact on productivity convergence and identified the strengths and weaknesses of related studies. From empirical evidence, this paper uses text analysis methods to measure the AI level of Chinese listed companies from 2001 to 2021, and verifies the positive role of AI at the enterprise level on productivity and address to overcomes the "Solow Paradox". Meanwhile this paper examining the impact of AI development at the enterprise level on the TFP convergence of Chinese listed companies, validating the role of AI in balanced and high-quality productivity development, and providing effective solutions to promote the integration of AI and industrial development.

Keywords: artificial intelligence (AI); productivity convergence; measurement; the Solow paradox.

1 Introduction

The concept of Artificial Intelligence (AI) was first proposed in 1956 and has been developed, through an initial period of slow development in the fields of logical reasoning and machine translation, followed by the era of expert system for autonomous learning and modeling. In recent years, it has rapidly advanced into the era of big data, autonomous learning, deep learning, and cognitive intelligence [1] [2]. From the current situation, AI mainly builds the infrastructure layer, algorithm layer and technology layer through computer technology and other means, and conducts machine learning with the help of knowledge and big data to mimic human physical and intellectual abilities [3]. Through the technological and economic characteristics: permeability, substitutability, synergy and innovativeness, AI has integrated cutting-edge advances in cognitive science, linguistics, computer science and neuroscience in its continuous iterative development [4], and it is also becoming an important driving force of this

Y. Feng et al. (eds.), *Proceedings of the 4th International Conference on Internet, Education and Information Technology (IEIT 2024)*, Atlantis Highlights in Social Sciences, Education and Humanities 26,
https://doi.org/10.2991/978-94-6463-574-4_10

scientific and technological revolution and industrial change, which has gradually changed the economic and social life [5]. Based on the strategic significance of AI, the major developed countries, such as the United States, the European Union and Japan, as well as developing countries, represented by new economies such as China and India, have elevated AI to a national strategy and introduced a series of supportive policies and promotional initiatives, all of which are aimed at seizing an advantage in the new round of technological revolution and strategic competition [1].

As an important engine for the new round of technological revolution and industrial change, AI has had a profound impact on innovation development and productivity improvement. It has provided a valuable shortcut for Chinese leapfrog development [2]. AI can promote productivity enhancement and industrial transformation and upgrading through various means, such as fostering innovation, facilitating technology spillovers, cultivating high-end production factors, creating high-end capital, and innovating production modes [4][6]. Therefore, while AI promotes productivity improvement in Chinese enterprises, does it also contribute to regulate the need for balanced productivity growth among enterprises? Does it address the unbalanced and insufficient development in the main contradictions? These questions deserve in-depth consideration and hold significant practical significance. From a research perspective, it is necessary to clarify whether the development of AI and its integration with traditional industries and other real economies can stimulate catch-up effects in low-efficiency enterprises, narrow the productivity gaps between enterprises, and foster convergence trends, thereby promoting balanced and high-quality development in the industrial economy.

To address the above issues, this paper reviews previous literature and findings from the perspective of AI development, productivity, and convergence. It reveals the shortcomings and deficiencies in existing studies regarding the impact of AI on firm-level productivity convergence, highlighting limited specific conclusions and empirical evidence. Therefore, this paper initially constructs a convergence model to examine the convergence of total factor productivity (TFP) among Chinese listed companies from 2001 to 2021. Then we use text analysis of annual reports from listed companies to extract data such as the frequency of AI-related keywords, measuring the level of AI development at the enterprise level. Based on such mentioned steps, this paper investigates the impact of AI on the convergence trend and speed of TFP among listed companies.

2 Literature Review of Enterprise AI and Productivity Convergence

2.1 The Solow paradox: the Development of Enterprise AI and Productivity

When discussing the impact of AI on productivity, it is inevitable to mention the "Solow paradox." Many previous studies have conducted a series of discussions on this topic, but scholars have not reached a consensus. Some studies argue that the "Solow paradox" between the development of AI and productivity does not always exist, and the overall impact of AI on productivity is positive. Acemoglu and Restrepo [7] deduced through theoretical models that the technological innovation of AI, such as industrial robots, can significantly enhance labor productivity by substituting for middle and low-end labor. Greatz et al., based on industry data from 17 countries between 1993 and 2007, also found that industrial robots improved labor productivity and total factor productivity[8].

In China, Li and Xu found that the increase in robot usage significantly improved labor productivity in Chinese manufacturing enterprises from 2000 to 2013 [9]. Qu and Lv reached similar conclusions and pointed out that enterprises adopting industrial robots tend to have stronger innovation capabilities, thereby promoting productivity improvement [10]. Mechanistically, Li et al., showed that AI can promote the improvement of manufacturing productivity by optimizing factor input structure and transforming production and management models [11]. Meanwhile, the application of AI reduces low-end assembly line positions and high-risk positions, increases the demand for high-skilled labor, and significantly enhances production efficiency while accelerating the accumulation of enterprise human capital [12]. Listed companies are also a key focus of research in this area. Some studies have shown that the development of AI has significantly improved the productivity of listed companies. The influencing mechanisms include labor quantity and the efficiency of material capital utilization [13], technological innovation output [14], and the facilitation of information transmission and flattening of management structures [15].

On the contrary, some researchers believes that the "Solow paradox" between the development of AI and productivity is well-founded [16]. Some studies have shown that in certain regions of China, there has been rapid growth in AI patent applications, but the growth of labor productivity in those regions has been relatively slow [17]. Other research has found that the development of AI did not enhance the productivity of Chinese manufacturing industry, and the "Solow paradox" was more evident in high-tech manufacturing sectors from 2011 to 2020 [11]. Also, there has no significant driving effect of AI on the total factor productivity in the pharmaceutical, computer, and instrument manufacturing industries from 2001 to 2017 [18].

Regarding the reasons for the "Solow paradox" between AI and productivity, Acemoglu and Restrepo believe that the application of technologies such as AI should align with the actual development of enterprises[19]. Excessive or inappropriate use may lead to improper allocation of capital and labor and stronger substitution effects, thus affecting the improvement of total factor productivity. Domestic scholars have also analyzed the reasons for the "Solow paradox", including the lagging effect of technological innovation [20], the accumulation of intangible capital in the early stage [16], productivity losses caused by mismatch between humans and machines [17], and the lack of human capital and market size constraints [11].

2.2 The Development of Enterprise AI and Productivity Convergence

However, whether from positive or paradox perspective, there is still a lack of research and findings on the convergence of AI's development and enterprise productivity.

Some scholars have conducted empirical research from the perspective of research and development (R&D) investment and found that R&D investment had a promoting effect on the convergence trend of labor productivity in Chinese industrial enterprises from 1999 to 2017. The driving effect of convergence was more significant in high-tech industries and had a stronger push for productivity convergence in industries with lower proportions of non-state-owned and state-owned property rights [21]. Other scholars have studied the convergence of productivity from the perspective of the digital economy at the regional and other levels. They found that the digital economy promoted labor productivity convergence by optimizing the employment structure of labor from 2013 to 2021. This optimization effect may exhibit nonlinear characteristics when considering the dynamic impact of population dividend transformation [22].

In summary, existing literature has conducted extensive research on the convergence of productivity and has provided relatively scientific and effective testing methods. Studies on the influencing factors of total factor productivity convergence have provided insights for the mechanism research in this paper. However, there are still some gaps and shortcomings in the research on the convergence of AI and productivity: (1) the technology of AI continues to evolve and innovate along with their integration with industries. The timeliness of existing literature in measuring the level of AI in domestic enterprises and its conclusions needs to be improved. (2) The "Solow paradox" of the impact of AI on domestic enterprise productivity is still under discussion, and there is limited empirical research and evidence at enterprise level. (3) The research on the impact of AI on the convergence of enterprise productivity is lacking, and there is a lack of targeted mechanism analysis.

3 Methodology

3.1 Model Construction

This paper primarily employs the commonly used σ-convergence and β-convergence models to examine the productivity convergence of Chinese listed companies from 2001 to 2021. Additionally, it considers AI variables to observe their impact on productivity convergence. σ-convergence is used to test the trend of total factor productivity (TFP) differences among different entities over time and to examine the dynamic characteristics of the dispersion degree of TFP distribution across regions. This paper uses the coefficient of variation as the index of σ-convergence. The specific model is as follows:

$$\sigma = \frac{\sqrt{\left[\sum_i^n \left(\ln TFP_{it} - 1/n \sum_i^n \ln TFP_{it}\right)^2\right]/n}}{1/n \sum_i^n \ln TFP_{it}} \tag{1}$$

TFP_{it} is the total factor productivity (TFP) for Chinese listed companies during the period is measured using the LP method, with 1 added when taking the natural logarithm. The results of σ-convergence reflect the distribution of company productivity during the period; the larger the value, the more dispersed the distribution. By comparing the values from different periods, we can observe the convergence trend of company productivity in the corresponding periods. If the values show a decreasing trend, it indicates that company productivity is converging during the corresponding period; otherwise, it is diverging. Unlike the σ-convergence method, β-convergence testing requires constructing a regression equation based on the relationship between the initial productivity value and the growth rate. The regression convergence coefficient is used to determine whether there is convergence in the TFP of companies over a certain period, and the corresponding convergence speed is calculated based on the convergence coefficient to analyze the convergence situation quantitatively [23][24]. First, the absolute convergence test equation for company productivity is constructed as follows:

$$\left(\ln TFP_{i,t} - \ln TFP_{i,t-T}\right)/T = \alpha + \beta \ln TFP_{i,t-T} + \varepsilon_{i,t} \tag{2}$$

$\left(\ln TFP_{i,t} - \ln TFP_{i,t-T}\right)/T$represents the annual average growth rate of total factor productivity (TFP) for the listed companies $i$during the period from $t-T$to t, with the value of T set to 1; $TFP_{i,t-T}$ is the TFP of the listed companies i at the initial period $t-T$; and$\varepsilon_{i,t}$ is the error term. Secondly, to conduct the conditional β-convergence test, we construct the regression equation with control variables based on equation (2) as follows:

$$\left(\ln TFP_{i,t} - \ln TFP_{i,t-T}\right)/T = \alpha + \beta \ln TFP_{i,t-T} + \Lambda X_{i,t} + \varepsilon_{i,t} \tag{3}$$

The above equation differs from the absolute β-convergence test equation in that it includes a series of control variables that may affect the growth of total factor productivity (TFP) in enterprises. These variables specifically include R&D investment (using the annual R&D expenditure rate), capital indicators (using the capital intensity of the enterprise), foreign trade dependency (the ratio of overseas business revenue to total operating revenue), and scale growth (using the total asset growth rate). The relationship between the β-convergence coefficient and the convergence speed is as follows: $\beta = -\left(1 - e^{-\lambda t}\right)$. Conversely, based on the estimated coefficient of β-convergence, we can calculate the convergence speed of total factor productivity (TFP) $\lambda = -\ln(\beta + 1)/t$, and the half-life required for productivity convergence $\tau = \ln(2)/\lambda$. This value is used to measure the time required for low-productivity enterprises to catch up with high-productivity enterprises and reach a steady state (absolute convergence), or the time required for each to reach a steady state within the overall environment (conditional convergence).

To examine the impact of AI on the productivity convergence of Chinese listed companies from 2002 to 2021, this paper refers to the methods of Yu [25] and Wang et al., [26] by directly incorporating enterprise AI development indicator into the β-convergence test equation. This approach allows for a more intuitive observation of changes in the convergence coefficient and the calculation of convergence speed. The specific regression equation is as follows:

$$\left(\ln TFP_{i,t} - \ln TFP_{i,t-T}\right)/T = \alpha + \beta \ln TFP_{i,t-T} + \gamma AI_{i,t-T} + \varepsilon_{i,t} \tag{4}$$

$$\left(\ln TFP_{i,t} - \ln TFP_{i,t-T}\right)/T = \alpha + \beta \ln TFP_{i,t-T} + \gamma AI_{i,t-T} + \Lambda X_{i,t} + \varepsilon_{i,t} \tag{5}$$

$\mathrm{AI}_{\mathrm{i,t-T}}$ represents the AI development indicator of the listed companies i at the initial period $t-T$. The coefficient γ directly reflects the impact of AI on enterprise productivity growth. By observing the changes from equations (2) and (3) to equations (4) and (5), we can determine the impact of AI on the direction and speed of productivity convergence in enterprises.

3.2 Measurement of Enterprise AI Variables

In terms of AI variable measurement, this paper references the AI development report by Tsinghua University AMiner team, which divides the AI field into ten categories: machine learning, natural language processing, knowledge engineering, information retrieval and recommendation, computer vision, speech recognition, robotics, data mining, human-computer interaction, and visualization. Relevant literature and bibliographies under each category were searched and compiled, resulting in a total of 188 specific keywords. For example, in the machine learning category, keywords include deep learning, model training, neural networks and etc, while in computer vision category, keywords encompass entity recognition, image understanding, image matching and etc. Considering potential biases from issues like duplicate extraction, experimental attempts on partial samples were conducted to further exclude invalid keywords, retaining 168 keywords. During the extraction of AI keyword frequencies from the annual reports of all listed companies from 2001 to 2021, 64 keywords with a total frequency of less than five were removed, leaving 104 keywords actually used to construct related indicators. The results show that besides "AI" as a high-frequency core keyword, the total frequencies of "intelligentization" and "robots" also exceeded that of "AI". The total frequencies of all other keywords were lower than that "AI".

The raw data for measuring the AI variable is the annual reports of Chinese listed companies from 2001 to 2021. The file names follow a uniform format that includes the year and company code. For reports with supplementary or correction announcements, the latest annual report file is used. The measurement process is specific as follows: An operating environment is built using the Pycharm software platform, and Python code is used to segment the annual reports of Chinese listed companies from 2001 to 2021. Based on this step, the total word count of each annual report is obtained, and the keyword frequency of the annual reports is counted to generate panel data with company codes as individuals, years as time, and various keywords as variable names. Based on the annual frequency data of 104 keywords for each listed company, we constructed three indicators to reflect the AI development trends of each company. First, a dummy variable is used, where 1 is assigned if AI-related keywords appear in the company's annual report, and otherwise is 0. Second, the frequencies of all AI keywords are summed. Third, the proportion of AI keyword count to the total word count of the annual report is calculated. In the baseline regression, we will first use the total keyword frequency as the AI indicator variable for listed companies to observe its impact on the convergence of total factor productivity (TFP).

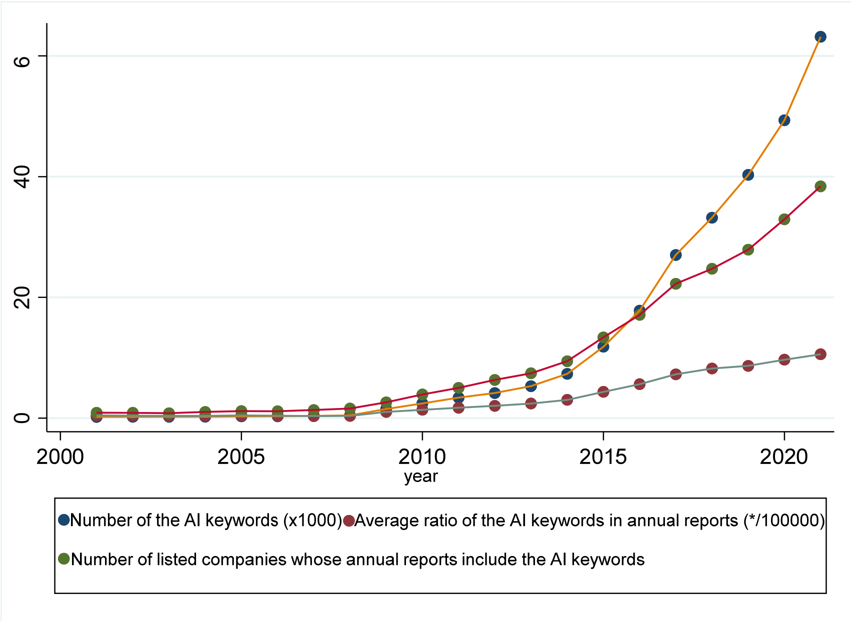
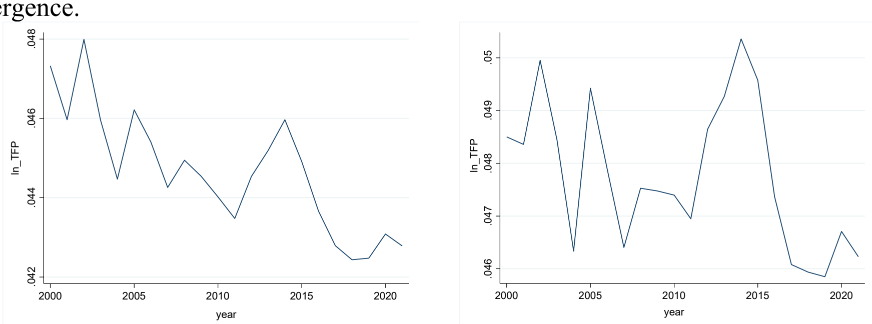


Fig. 1. Changes in AI Development Indicators for Chinese Listed Companies from 2001 to 2021

According to Figure 1, it shows that the attention to AI among Chinese listed companies increased year by year from 2001 to 2021. In 2001, only 89 companies mentioned AI-related keywords in their annual reports, accounting for less than 10% of the total number of listed companies. This number surpassed 200 companies in 2009, 500 in 2011, 1,000 in 2015, and directly exceeded 3,000 in 2020. In 2021, more than 3,800 companies mentioned AI, accounting for over 80% of the total number of listed companies in China. Looking at the total frequency of AI keywords in all company annual reports, there were 207 keywords in 2001, averaging 0.18 keywords per listed company. This number surpassed 1,000 keywords in 2009, 10,000 keywords in 2015, and exceeded 60,000 keywords in 2021, representing an approximate 300-fold increase compared to 2001. The proportion of AI keywords in the total word count of annual reports also grew from less than 0.0005% in 2001, to rapidly surpass 0.001% in 2009, and reached over 0.01% in 2021.Therefore, from 2001 to 2021, the degree of attention to AI among Chinese listed companies not only continuously increased but also displayed two main phases: a period of slow and fluctuating growth before 2008, and an accelerated growth period after 2009.

4 Empirical Results

By observing the recalculated results of σ-convergence productivity for Chinese listed companies from 2001 to 2021 (Figure 2), it is evident that the convergence coefficient for the full sample of listed companies exhibits irregular fluctuations, with no clear σ-convergence characteristics. However, the convergence coefficient for listed manufacturing companies shows a trend of fluctuating decline, indicating periodic convergence characteristics. The σ-convergence results indicate that the trend of total factor productivity (TFP) convergence for Chinese listed companies from 2001 to 2021 is irregular, with varying degrees of dispersion. Although the coefficient variation for TFP in listed manufacturing companies fluctuates, the overall trend is towards convergence.



(1) (2)

Fig. 2. σ-convergence Test of Total Factor Productivity for Listed Companies (2001-2021)

Note: (1) represents results for manufacturing only, (2) represents results for the full sample.

The next step is to examine the β-convergence test. Table 1 reports the regression results of absolute and conditional β-convergence, as well as the results after including the AI variable. According to columns (1) and (3), the β coefficients are negative, indicating that the productivity of Chinese listed companies showed a β-convergence trend from 2001 to 2021, satisfying both absolute and conditional convergence characteristics, with the absolute value of the conditional convergence result being slightly lower.

In terms of convergence speed, the productivity convergence speed of companies during absolute β-convergence regression is $0.00875 = -\ln(-0.16059 + 1)/20$, and the half-life of productivity convergence is $79.19147 = \ln(2)/0.00875$; during conditional β-convergence regression, the productivity convergence speed is $0.00851 = -\ln(-0.15645 + 1)/20$, and the half-life of productivity convergence is $81.48149 = \ln(2)/0.00851$. Comparing the results after including AI in columns (2) and (4), it is shown that for both absolute and conditional β-convergence, the direction of the convergence coefficient remains negative and its absolute value increases. After considering the impact of AI, the calculated absolute convergence speed and conditional convergence speed of productivity are $0.00887 = -\ln(-0.1626 + 1)/20$ and $0.00860 = -\ln(-0.15804 + 1)/20$, respectively, showing increases of 1.37% and 1.06% compared to results without considering the AI variable. The half-life of productivity convergence also reduced to $78.12159 = \ln(2)/0.00887$ and $80.58784 = \ln(2)/0.00860$, respectively. It reveals that the inclusion of AI further accelerated the productivity convergence speed of listed companies, effectively reducing the half-life of productivity convergence.

Table 1. β-convergence Test Results of TFP for Listed Companies and the Impact of AI

	(1) $\Delta \ln TFP$	(2) $\Delta \ln TFP$	(3) $\Delta \ln TFP$	(4) $\Delta \ln TFP$	(5) $\Delta \ln TFP$	(6) $\Delta \ln TFP$
$l.\ln TFP$	-0.16059***	-0.16260***	-0.15645***	-0.15804***	-0.16106***	-0.15674***
	(0.00536)	(0.00547)	(0.00622)	(0.00626)	(0.00555)	(0.00635)
AI		0.00006**		0.00008**	0.00138**	0.00118**
		(0.00003)		(0.00004)	(0.00063)	(0.00059)
$l.\ln TFP \times AI$					-0.00057**	-0.00047*
					(0.00027)	(0.00025)
Asset			0.01401***	0.01400***		0.01399***
			(0.00129)	(0.00129)		(0.00129)
RDpro			-0.02563**	-0.03440***		-0.03468***
			(0.01283)	(0.01327)		(0.01326)
KI			-0.00034	-0.00034		-0.00034
			(0.00023)	(0.00023)		(0.00023)
AbroadRev			0.02053***	0.02005***		0.02007***
			(0.00282)	(0.00283)		(0.00283)
_cons	0.37629***	0.38057***	0.36503***	0.36841***	0.37695***	0.36538***
	(0.01225)	(0.01248)	(0.01438)	(0.01446)	(0.01267)	(0.01467)
N	33949	33949	33949	33949	33949	33949
R^2	0.089	0.090	0.143	0.144	0.090	0.144
adj. R^2	0.089	0.090	0.143	0.144	0.090	0.144
F	898.53065	448.89909	212.96333	178.81209	301.17481	153.65299

Note: All AI indicators are based on AI keyword frequency; Standard errors in parentheses， $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

To substantiate the promoting effect of AI indicators on the productivity convergence of listed companies, we included the interaction term between the AI indicator variable and the initial productivity variable in regression equations (3) and (4). This was done to observe the regression coefficients of the interaction terms from the perspective of moderation effects [22]. According to columns (5) and (6), the coefficients of the interaction terms between AI indicator variables and initial productivity variables are significantly negative, indicating that the inclusion of AI variables indeed further increases the absolute value of the convergence coefficient (negative), thereby enhancing the convergence speed. Additionally, observing the regression coefficients of the AI indicator variable in each column, it reveals that the development of AI from 2001 to 2021 can generally promote the growth of total factor productivity (TFP) of companies, with all results being significant. If the entire sample is grouped by the median annual productivity, and regressions are conducted separately for high-productivity listed companies and low-productivity companies, the related conclusions can be further verified. According to Table 2, during the sample period, both high and low productivity companies exhibit significant conditional β-convergence characteristics. The absolute value of the convergence regression coefficient within the low-productivity company group is higher than that of the high-productivity company group, indicating a faster convergence speed. The impact of AI indicator variables also differs between the two types of companies, with AI significantly and more strongly promoting the TFP growth of low-productivity companies.

Table 2. β-convergence Test Results of TFP for Listed Companies and the Impact of AI (Grouped)

	(1) $\Delta \ln TFP$	(2) $\Delta \ln TFP$	(3) $\Delta \ln TFP$	(4) $\Delta \ln TFP$	(5) $\Delta \ln TFP$	(6) $\Delta \ln TFP$
$l.\ln TFP$	-0.25584***	-0.31847***	-0.25662***	-0.32074***	-0.23672***	-0.18788***
	(0.01010)	(0.01272)	(0.01013)	(0.01278)	(0.01129)	(0.00933)
AI			0.00005	0.00015***		
			(0.00004)	(0.00004)		
Asset	0.01152***	0.01219***	0.01152***	0.01220***	0.01165***	0.01464***
	(0.00144)	(0.00190)	(0.00144)	(0.00191)	(0.00161)	(0.00235)
RDpro	0.09275***	-0.00196	0.08356***	-0.01460	-0.02440	-0.04412
	(0.01619)	(0.01575)	(0.01716)	(0.01591)	(0.01519)	(0.03220)
KI	-0.00656***	-0.00024	-0.00657***	-0.00024	-0.00247*	-0.00027
	(0.00089)	(0.00020)	(0.00089)	(0.00020)	(0.00127)	(0.00018)
Abroad-Rev	0.01211***	0.02457***	0.01188***	0.02376***	0.02746***	0.01489***
	(0.00284)	(0.00345)	(0.00283)	(0.00347)	(0.00430)	(0.00446)
_cons	0.62657***	0.70422***	0.62829***	0.70868***	0.55806***	0.43374***
	(0.02390)	(0.02811)	(0.02395)	(0.02823)	(0.02699)	(0.02141)
N	17725	16224	17725	16224	16063	17886
R^2	0.337	0.221	0.337	0.223	0.238	0.140
adj. R^2	0.337	0.221	0.337	0.222	0.238	0.139
F	176.30456	180.71157	147.36438	151.25413	137.49148	119.68179

Note: Columns (1) and (3) are regression results for the high-productivity company sample, columns (2) and (4) are regression results for the low-productivity company sample, column (5) is the regression result for the AI company sample, and column (6) is the regression result for the non-AI company sample; Standard errors in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Based on whether the annual reports of companies contain AI-related keywords, relevant companies are identified as AI-related companies. This allows for a focused study on the convergence of their total factor productivity (TFP), with non-AI companies serving as a reference group for comparative analysis. Columns (5) and (6) in Table 2 present the regression results from experiments conducted following this approach. It reveals that both AI-related companies and non-AI-related companies exhibit significant conditional β-convergence in TFP during the sample period, with the absolute value of the convergence regression coefficient for AI-related companies being higher than that for non AI-related companies. Specifically, the productivity convergence speed for AI-related companies is $0.01351 = -\ln(-0.23672 + 1)/20$, with a half-life of productivity convergence of $51.31946 = \ln(2)/0.01351$，; for non-AI-related companies, the productivity convergence speed is $0.01041 =$

$-\ln(-0.18788 + 1)/20$, with a half-life of productivity convergence of $66.61445 = \ln(2)/0.01041$.

Although this result cannot directly confirm the positive impact of AI on the convergence of the entire company sample, it reflects that companies with an inclination towards AI development and relevance indeed exhibit a stronger convergence trend in productivity. As a result, it can be concluded that the development of AI from 2001 to 2021 has significantly promoted the improvement of TFP levels among Chinese listed companies and has also played a positive role in the balanced development of corporate productivity.

5 Conclusion

The main research conclusions are as follows:

First, from 2001 to 2021, the development of AI among Chinese listed companies experienced a period of slow fluctuation and rise until 2008, followed by a rapid growth phase. Until recent years, it has shown an accelerating trend and reflects the potential of AI development in China.

Second, during the period from 2001 to 2021, the σ-convergence characteristics of productivity among Chinese listed companies were not significant, but the TFP of listed manufacturing companies exhibited phased σ-convergence characteristics, with the overall gap in TFP among companies showing a narrowing trend. During this period, Chinese listed companies passed β-convergence test for TFP, satisfying both absolute and conditional convergence characteristics, with low-efficiency companies showing a catch-up effect towards high-efficiency companies.

Third, AI had a significantly positive impact on TFP of Chinese listed companies, with a stronger effect on the TFP growth of low-productivity companies, which promoted the catch-up effect of low-efficiency companies towards high-efficiency companies. AI further accelerated β-convergence speed of TFP among listed companies and reduced the half-life of productivity convergence. This result suggests that AI development not only overcomes the "Solow Paradox" but also helps achieve balanced development of corporate productivity.

References

1. Zhang L.P,Zhang X.Y.(2023).Research on the Effect and Mechanism of Artificial Intelligence Affecting the Economy: From the Perspective of Literature Review.Science and Technology Management Research, 43(11): 169-176.
2. Li L, Xu D.C. (2020).Can robots improve labor productivity?Mechanism and facts. Industrial Economics Research, (03):127-142. DOI:10.13269/j.cnki.ier.2020.03.010.
3. Geng Z.H. (2021). Artificial Intelligence and High-quality Industry Development in China: An Empirical Analysis Based on Industry Upgrade and Industry Structure Optimization. Macroeconomics, (12):38-52+82. DOI:10.16304/j.cnki.11-3952/f.2021.12.003.
4. Shi B. (2020). An Explanation of the Mechanism of AI Promoting Economic High-quality Development.Reform, 2020 (01):30-38.

5. Cai Y.Z, Chen N.(2019). Artificial Interlligence and High-quality Growth & Employement in the Era of New Technological Revolution. The Journal of Quantitative & Technical Economics (05), 3-22. doi:10.13653/j.cnki.jqte.2019.05.001.
6. Luo X.B. (2022). Internet Development and Productivity Growth of Manufacturing Industry: A Mechanism Study Based on the Process of Marketization . Contemporary Finance &Economics, (05):113-123.DOI:10.13676/j.cnki.cn36-1030/f.2022.05.010.
7. Acemoglu D, Restrepo P. (2018). The race between man and machine: Implications of technology for growth, factor shares, and employment. American economic review, 108(6):1488-1542.
8. Graetz G, Michaels G.(2018). Robots at work. Review of Economics and Statistics, 100(5):753-768.
9. Li L, Xu D.C. (2020).Can robots improve labor productivity?Mechanism and facts. Industrial Economics Research, (03):127-142. DOI:10.13269/j.cnki.ier.2020.03.010.
10. Qu X.B, Lv J.N.(2022).The Effect of Robotics Application on Enterprise Productivity and Innovation. Academic Exploration, (08):90-99.
11. Li X,et al.,(2023). How AI Improves the Quality of China's Manufacturing Development: Re-examination of Solow Paradox in China's Manufacturing. Journal of Lanzhou University (Social Sciences), 51(04):44-58. DOI:10.13885/j.issn.1000-2804.2023.04.004.
12. Shao W.B, et al.(2018). Informationization and the Demand for Skilled Labor: Empirical Evidence Based on Micro-level Enterprises in China. Economic Review, (2): 15-29.
13. Fan X. N, et al.,(2020).The Impacts of Artificial Intelligence on the Productivity of Manufacturing Firms: Is There a Productivity Paradox.Science & Technology Progress and Plicy,37(14):125-134.
14. Zhang L.P,Zhong Y.L.(2023). Impact of Artificial Intelligence Application on Total Factor Productivity from the Perspective of Value Chain——Empirical Research Based on Chinese A-Share Listed Companies. Reform of Economic System, (04):106-113.
15. Zheng Q.J,Wang G.F.(2021). Application of Artificial Inteligence Technology and Productivity of Chinese Manufacturing Enterprises.Study and Practice,(11):59-69. DOI: 10.19624/j.cnki.cn42-1005/c.2021.11.006.
16. Cheng W.(2021).Artificial Intelligence, Solow Paradox and High-quality Development. Economic Research Journal,56(10):22-38.
17. Hu S.M, et al.,(2021). Artificial Intelligence Application, Human-machine Collaboration and Labor Productivity. Chinese Journal of Population Science, (05):48-62+127.
18. Jiang W, Li P. (2022). AI and TFP: "Technology Dividend" or "Technology Gap". Journal of Statistics and Information, 37(05):26-35.
19. Acemoglu D, Restrepo P. (2019). Automation and new tasks: How technology displaces and reinstates labor. Journal of Economic Perspectives, 33(2): 3-30.
20. Guo M, Fang M.R.(2018). Artificial Intelligence and Productivity Paradox: International Experience. Reform of Economic System, (05):171-178.
21. Li D.D.(2020).Comparative Analysis of the Effect of R&D Input on Industrial Productivity Convergence in China. Soft Science,34(09):37-42. DOI: 10. 13956/ j.ss. 1001-8409.2020.09.06.
22. Yang X,Zhao S.G.(2023). The Impact of Digital Economy on Labor Productivity Convergence: Viewing from the Perspective of Demographic Dividend Transition. Chinese Journal of Population Science, 37(02):3-18.
23. Barro R J, Sala i Martin X. (1992). Convergence. Journal of political Economy, 100(2): 223-251.
24. Miller S M, Upadhyay M P. (2002).Total factor productivity and the convergence hypothesis. Journal of Macroeconomics, 24(2): 267-286.

25. Yu Y. Z.(2015). Study on the Dynamic Spatial Convergence of Total Factor Productivity Across Chinese Provinces. World Economy, 38(10): 30-55. DOI: 10. 19985/ j. cnki. cass-jwe.2015.10.003.
26. Wang K,e t al. (2022). Tourism Technical Efficiency, Tourism Green Productivity Convergence, and Its Influencing Factors. Economic Geography, 2022, 42(06): 215-224. DOI: 10.15957/j.cnki.jjdl.2022.06.022.