

Artificial Intelligence and Enterprises' Involutionary Competition

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Abstract. Although the amount of investment by companies in artificial intelligence has risen significantly in recent years, the speed at which these companies are adopting AI varies; therefore, many "intelligent" enterprises have appeared with considerable differences in performance. Chinese A-share listed companies will be taken as the subjects of the research, and in conjunction with text analysis, the intensity of AI application at all levels will be used to investigate changes in overall involutionary competition and specific types of firms. Therefore, AI has reduced the competition among the insiders to some extent. The three are to make better use of resources and reduce transaction costs; to spread knowledge spillovers and promote collaborative innovation in the supply chain; and to improve the efficiency of factor allocation and restore market-clearing mechanisms. Based on the analysis of heterogeneity, the inhibitory effect of AI on involutionary competition is mainly observed in non-heavy-polluting, technology-intensive enterprises, and it is not significant in heavy-polluting, asset-intensive and labour-intensive enterprises. Moving away from the simple model put forward in the previous studies that directly links AI to firm performance, this paper first applies AI to the study of inter-firm competition to offer new theoretical ideas on how technological change affects the competitive environment. It can also give the company a reason to consider the competitive effect of using AI in the digital economy more carefully and help the regulator formulate appropriate competition policies.

Keywords: Artificial intelligence, cutthroat competition, resource allocation efficiency, supply chain knowledge spillover, technological heterogeneity

1. Introduction

Global investment in artificial intelligence has exceeded 400 billion US dollars each year for the past three years, has increased at a rate of over 25% annually, and businesses have been showing strong interest in using this new technology. However, at the same time, the reality is rather bleak: more than 70% of the companies' AI projects are still in the trial stage and have not been scaled up; among those that have been deployed, nearly 60% have not shown clear profit improvements. Irony is that with the convergence of open-source algorithmic architecture and centralised supply of computing infrastructure, many enterprises have started to adopt a very standardised AI deployment model. Although it was hoped that this technology would increase efficiency, it has not created any

new competitive advantages; instead, it has led to more uniform capital investment and reduced the marginal returns on R&D investment and innovation paths have converged.

Involuntary competition is a type of inefficient competition that continually increases inputs but reduces the efficiency of output; innovative behaviour is suppressed by imitation, and differentiation strategies are eroded in homogeneous competition. In fact, continuous capacity-price competition in manufacturing has squeezed industry profits; competition for traffic in the internet platform economy has become a zero-sum game; and unnecessary investment in new-generation technology has further wasted resources. The main harm of such competition is a self-reinforcing lock-in effect: firms will engage in a cycle of price wars and imitative innovation, the logic of short-term survival will replace that of long-term strategic planning, and thus the growth of total factor productivity will slow down. At the micro level, involuntary competition is caused by herd behaviour resulting from information asymmetry and managerial myopia. Many previous studies have investigated the effects of changes in market structure or institutions on this issue, but little attention has been paid to how technological change is altering the strategic interaction of enterprises. Promptly address the lack of theoretical basis in the current work.

Artificial intelligence can be applied to the spirit of "neijuan" in a different way, and through this, many more subtle theoretical links that are not immediately obvious can be uncovered, as well as blind spots in the current literature. On the one hand, AI is very good at integrating information and can help the company find specific market niches to improve the accuracy of differentiated operations and reduce internal competition. At the same time, with the spread of open-source algorithms and cloud computing, many companies can use functionally equivalent decision-making systems at a very low cost. Given the increase in the amount of information, widespread convergence of the decision-making reference frame is likely to occur, strategic imitation will be promoted, and thus, Neijuan will face a decline. Although both predictions are logically correct in isolation, current research has either limited the application of AI to internal operational efficiency or attributed the competition at Neijuan to external market forces; thus, AI as a way to change inter-firm strategic interaction has not been studied. This theoretical gap will provide an introduction to the research in this paper.

Listed companies on the Chinese Shanghai and Shenzhen A-share markets will be taken as the sample, and both text analysis and financial data will be used to examine the extent of application of artificial intelligence (AI) and the degree of involuntary competition. Empirically study the effect of artificial intelligence on inimitable competition and all its attributes. The three main problems of the research are as follows: Does AI alter the intensity of firms' involuntary competition? If so, does it generally reduce or enhance this type of competition? Are there any differences among industries with different characteristics? The theoretical and practical values of this study are the same. Most of the theoretical studies abroad have concentrated on absolute measures of performance, such as labour productivity and total factor productivity, in their research on artificial intelligence, and have paid less attention to the relative positions of different companies. A competition-dynamics perspective on the analysis of technological effects is added to promote the integration of diffusion theory and industrial organisation theory in this paper. Another reason for investment competition at the micro level is technological change; we can gain a better understanding of this phenomenon and learn about the internal drivers of AI in shaping competitive patterns; thus, new directions for future theoretical research have also been revealed. In practice, the above results can help companies form reasonable expectations of the competitive situation resulting from the use of artificial intelligence and avoid being led by the wave of technological changes. At the same time, it will provide

supporting data for the government in developing appropriate competition regulations to address the common problems of AI in the industry.

2. Literature review

The foundation for the study of how technological innovation affects the order of market competition is rooted in economics and management. Artificial intelligence is now a very representative general-purpose technology that is changing the basic logic of economic development and the fundamental patterns of corporate competition to a certain extent. At the same time, "involutionary" competition has formed a kind of market disorder under specific institutional conditions and has also become a serious obstacle to high-quality development in some areas of China. In terms of the concept definition, people's understanding of artificial intelligence has changed from technical attributes to the analysis of its economic effects. Luo Yangfan and others have shown that the technological effect of AI is to change all-round production functions, modify the way factors of production are distributed, and reorganize inter-organizational relations [1]. Based on the above research, this paper believes that AI should be understood in an economic sense as a compound force that includes both technological advancement and social integration; that is to say, it is a collection of technologies with the power to increase efficiency, spread knowledge, and optimize resource allocation, but it is also a system that needs to be adapted by organisations and supported by institutions and markets to achieve its full positive effects. Li Zhaochen believes that, according to the theory of market failure, "involutionary" competition is a typical type of economic disorder caused by many failures in the supply-side signalling mechanism, demand-side feedback mechanism and institutional guidance mechanism [2]. Zhao Xian and others have formed an imitation-underpricing and anti-innovation alliance with the lower end of the market [3]. This paper thinks that "involutionary" competition should be defined as a state of competitive disorder caused by the combination of institutional defects and market failures, and it has the following characteristics: low-level homogeneity of competition and zero-sum games. It is an organised reduction of the incentive for innovation, a misallocation of resources, and continuous obscuring of market signals; therefore, it is an institutional problem that is fundamentally different from the high-competition environment in economics.

Research on the effect of artificial intelligence has been carried out systematically at home and abroad in recent years. Liu Jin and others have found that AI has both the effect of job loss and job creation at the labour market level, and medium-skilled workers are most at risk of being replaced; thus, employment polarisation has occurred [4]. Ma Yaming and others have pointed out that the three reasons for the development of AI technology at the enterprise level are technological empowerment, governance optimisation and risk adaptation [5]. Wang Xiaoxia and others have shown through the concept of data factor marketisation that improving the efficiency of factor supply, promoting "AI+" integrated innovation, and strengthening the data governance environment can all boost enterprise AI innovation [6]. Based on the above studies, it can be seen that the influence of AI on the economic system now extends to many places, including boosting innovation, organising supply chains, optimising capital allocation, etc., and does not only increase production efficiency directly. However, the full extent of the effect of technology will also be limited by institutional conditions and the initial state of market structure.

Research has made some progress in the past on the origins and economic effects of "involutionary" competition. Zhou Jing, in terms of the type of formation, divides it into four categories based on the dimensions of "competition type" and "driving factors": firm-driven price competition, policy-induced price competition, firm-led capacity expansion, and policy-driven

overcapacity, and these have different formation processes [7]. Zhang Jinchang and others believe that involutionary competition reduces the continuous innovation ability and market efficiency of enterprises in terms of total factor productivity, thus impeding the growth of productivity; this negative effect is more pronounced in low-tech industries, sectors with high customer concentration and markets at a low level of monopoly [8]. Shen Hongliang and others have empirically shown that, through digitalisation and reduction of information asymmetry, involutionary competition can be weakened; thus, innovation efficiency has been increased and cross-regional capital flows have been promoted, and this effect is relatively stronger in areas with more developed financial markets and less market segmentation [9].

Based on the combination of the two above strands of literature, it can be seen that artificial intelligence and "involutionary" competition are related in many ways. However, there is a lack of research on this issue so far. Most of the research on the impact of artificial intelligence has focused on the direct effects, such as productivity, employment, innovation and supply chains, and has not explicitly mentioned "involutionary" competition in its analysis. Therefore, it is unknown whether or not the effect of technology diffusion changes in an involutionary environment, and how it does so. At the same time, although research on the governance paths of digital transformation has examined involutionary competition, few have focused on using artificial intelligence as the main tool to change the competitive environment.

3. Mechanism analysis and hypothesis formulation

Reduce the cost of doing business and lower prices by using artificial intelligence to help lower them. The reason for this internal competition in pricing is that, given the same model of resource allocation, the companies are unable to set different prices and are thus forced to engage in a price war at the bottom end of the cost spectrum. Therefore, there will be excessive marketing expenses and an increase in bad debts, reducing the quality of the product. With the introduction of AI systems, enterprises are moving away from the old mode of total-cost control, investigating the reasons for resource consumption at the operational level, accurately identifying inefficient capacity and non-value-added activities, and setting different resource allocation plans according to the various production processes and positions in the customer value chain. As companies have created all sorts of input structures by means of AI-assisted personalised optimisation paths, the basis for homogeneous price competition has been broken; therefore, each enterprise can set its own price floor according to various cost advantages and avoid the vicious circle of mutual price undercutting. At the same time, AI can also learn about cost behaviour to help management distinguish between strategic investments in costs and tactical reductions in costs; thus, it is possible to avoid cutting essential parts, such as research and development and employee training, in a price war and focus instead on value creation. Therefore, with improved efficiency in resource allocation and a reduction in transaction costs, the problem of low-price internal competition can be alleviated, and the company will be freed from the vicious circle of high sales and increasing losses.

Artificial intelligence can help solve the problems of homogeneity and low-tech content in the domestic competition of enterprises by promoting knowledge spillovers and collaborative innovation in the supply chain. A typical feature of inward competition in terms of innovation is that most enterprises fall into a path-dependence of imitation and trend-following; thus, R&D investment is highly concentrated, products and services lack differentiation, and technological progress is stagnant at a low level due to repeated improvements. To keep up with the times, some enterprises have begun to export low-quality, low-priced goods and compete fiercely for well-paid employees. The main direction of technological innovation in the focus company is incremental, and there is

little impact on its upstream and downstream partners. The above reasons motivate suppliers to break away from traditional path dependencies in light of the new demands for technology and change the mode of cooperation, so they can achieve gradual innovation by introducing intelligent equipment and optimising production processes. Promote the development of new technologies through the sharing of resources in industry-academia-research cooperation and distribute the risks of funding among the ecosystem of these institutions. The AI innovations in the top company are being spread through improvements in the skill structure and information systems of the workforce, motivating clients to increase the proportion of high-skilled employees and strengthen digital infrastructure to meet the manufacturing demands for intelligent intermediate goods and new demands from end markets. Vertical diffusion of knowledge spillovers in the supply chain has broken the silos of innovation among enterprises and promoted the efficient spread of technical standards and management ideas throughout the chain. Firms can then make different technological improvements based on a common knowledge foundation, avoid redundant investment at the same level of technology, and shift the focus of competition from imitation and reproduction to original creation. Therefore, it will be possible to solve the problems of low-end lock-in and inefficient repetition in inward competition systematically.

Artificial intelligence can reduce the waste of resources by improving the efficiency of factor allocation and strengthen the signal transmission of the market. The reason is that the competition has distorted the market signals and limited factor mobility; thus, enterprises cannot decide on the supply and demand of goods and services by way of price signals alone, and essential resources, such as capital and labour, fail to be concentrated in high-productivity sectors, leaving many units of production factors stranded in low-efficiency surplus capacity. Artificial intelligence is used to process data and make predictions to help the company better understand changes in market supply and demand, adjust production plans and inventory in a timely manner according to updated demand signals, and thus reduce the problem of cyclical overcapacity. At the same time, AI will also continue to develop in accordance with changes in technology and competition; thus, we can gain a long-term view of the company's value and shift investment away from repetitive, low-end development towards areas that have genuine technological barriers and high growth potential. More importantly, the openness of the information released by AI has helped to prevent unfair competition in disclosure and administrative barriers; thus, market prices can once again serve the basic function of signalling real values. Therefore, to improve the factor allocation efficiency and restore the market signalling function, institutional support for cutthroat competition should be reduced; enterprises will move from zero-sum competition in the existing market to a positive competition model based on efficiency improvement and value creation.

Hypothesis 1: The extent of application of artificial intelligence technology is inversely related to the intensity of internal competition in a company.

4. Variable specification and model selection

4.1. Data source

The data in this paper come from A-share listed companies in China between 2012 and 2024. The following steps were taken to process the data: (1) Companies that were ST or *ST were excluded; (2) Samples with obviously abnormal financial data were removed; (3) Samples without data for the statistical year were deleted; (4) To reduce the possible impact of extreme values on the test results, the top 1% and the bottom 1% of continuous variables were Winsorised. All the variable data were

obtained from the Wind and CSMAR databases, and Stata 19.0 econometric software was used to conduct the data analysis.

4.2. Variable setup

The independent variable of this study is the extent of application of artificial intelligence (AI) by enterprises. Following the method of Yao Jiaquan and others, we measure the extent of AI application by counting the number of AI-related keywords in the annual reports of listed companies [10]. Take the logarithm of the raw word frequencies to obtain the AI index ($\ln words$), and a larger value indicates that the word is used more frequently in AI. The dependent variable is "involutionary" competition ($InvC$) by firms. Based on the previous studies, we use the entropy method to comprehensively evaluate the strength of involutionary competition in the four aspects of capacity utilisation, transaction costs, capital investment efficiency and labour investment efficiency.

The control variables in this paper are firm size ($Size$), leverage (Lev), profitability (ROA), firm age ($FirmAge$) and market-to-book ratio ($TobinQ$).

4.3. Model selection

To study the effect of the level of artificial intelligence (AI) application by firms on their "involutionary" competition ($InvC$), a time-fixed effects regression model is employed, and the following regression model is set up:

$$InvC_{it} = \beta_0 + \beta_1 * AI_{it} + \sum \alpha_k controls_{it} + \lambda_t + \varepsilon_{it} \quad (1)$$

Here, $InvC_{it}$ represents the degree of involutionary competition for firm i in year t ; AI_{it} denotes the level of AI application for firm i in year t ; ε_{it} is the random error term; i and t represent firm and year, respectively. The model also controls for year fixed effects λ_t , where k indicates the number of control variables, β_0 is the constant term, and β_1 is the coefficient of the independent variable.

5. Empirical analysis

5.1. Descriptive statistics

Table 1 shows the descriptive statistics of the variables, and it can be seen that the mean of the independent variable AI is 0.905; therefore, the general level of artificial intelligence application among the sample firms is relatively low. The standard deviation of the independent variable is 1.164; therefore, there are considerable differences among the individual firms and this variable is not uniform. The mean of the dependent variable $InvC$ is 0.049; therefore, most firms in the sample have a relatively low level of internal competition, but there is still some variation among individuals. The reasons for this difference may be various factors in the independent variable or caused by unobserved factors such as industry, region and management. Generally speaking, the statistical properties of the control variables are the same as in the previous studies, so they can be used as a reliable data foundation for the following empirical analysis.

Table 1. Descriptive statistics table

Variable	Obs	Mean	Std.Dev.	Min	Max
InvC	23145	0.049	0.043	0.011	0.239
AI1	23145	0.905	1.164	0	5.030
Size	23145	22.228	1.177	19.478	26.484
Lev	23145	0.403	0.188	0.038	0.937
ROA	23145	0.038	0.067	-0.485	0.255
TobinQ	23145	2.095	1.314	0.787	17.729
FirmAge	23145	3.001	0.296	1.609	3.714

5.2. Benchmark regression

Table 2 shows the baseline regression results of the effect of artificial intelligence (AI) on corporate involutory competition (InvC). Column (1) only includes the main explanatory variable, and the estimated coefficient for AI1 is -0.0029; it is significantly negative at the 1% level. Columns (2) to (4) successively add firm fixed effects, firm-level control variables and year fixed effects; the coefficient for AI1 is still -0.0029 and -0.0026, respectively, all of which pass the 1% significance test, and it can be concluded that AI has a negative effect on corporate involutory competition. Regarding the scale of the economy, as shown in column (4), the coefficient for AI1 is -0.0026; that is, a 1% rise in the level of AI development will reduce InvC by approximately 0.000026 units. The decrease from the sample mean of InvC at 0.0759 is about 0.034 per cent. Although the economic scale is small, given that involutory competition is affected by many factors and the rate of change of logged variables is inherently limited, the effect is still highly statistically significant and thus provides some useful information and empirical support for hypothesis H1.

Table 2. Benchmark regression analysis table

	(1)	(2)	(3)	(4)
	InvC	InvC	InvC	InvC
AI1	-0.0029*** (0.00)	-0.0029*** (0.00)	-0.0028*** (0.00)	-0.0026*** (0.00)
Size			-0.0007** (0.00)	-0.0007** (0.00)
Lev			-0.0092*** (0.00)	-0.0094*** (0.00)
ROA			0.0077 (0.00)	0.0071 (0.00)
TobinQ			0.0012*** (0.00)	0.0012*** (0.00)
FirmAge			-0.0047*** (0.00)	-0.0032*** (0.00)
_cons	0.0513*** (0.00)	0.0513*** (0.00)	0.0830*** (0.01)	0.0759*** (0.01)
N	23145	23145	23145	23145
R ²	0.006	0.003	0.014	0.016

Table 2. (continued)

year	no	no	no	yes
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Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

5.3. Robustness check

The five components of the robustness checks in this paper are: measurement of variables, endogeneity, addition of control variables, regional fixed effects and statistical inference (Table 3). All models contain firm size, debt level, profitability, growth outlook, firm age and year fixed effects. Column (1) is an alternative indicator for AI1, and this one is $\ln(\text{sum of 73 AI-related keyword frequencies in MD\&A} + 1)$ for the test. The coefficient is -0.0027 and, at the 1% level, this result is not dependent on measurement error. Column (2) is a one-lagged AI1 to deal with reverse causality, and the lagged term is still significantly negative; thus, the inhibition of competition by AI has a time lag. Column (3) is for the largest shareholder's ownership and board size; the coefficient of AI1 is -0.0025 and significant at the 1% level, so omitting other governance factors does not change the main results. Column (4) is a provincial dummy variable to account for time-invariant regional differences; the coefficient of AI1 is still -0.0025 and significant at the 1% level, and the model fit has improved. Column (5) is a heteroskedasticity-robust standard error, and the coefficient of AI1 is -0.0026 and has not changed after adjustment. Through various substitutions of variables, lagging, addition or exclusion of control variables, regional fixed effects and standard error adjustment, it was found that the negative effect of AI1 on involutory competition (InvC) remains consistently between -0.0025 and -0.0027 and is significant at the 1% level; thus, the original conclusion is confirmed. Heterogeneity Analysis.

Table 3. Robustness test analysis table

	(1)	(2)	(3)	(4)	(5)
	InvC	InvC	InvC	InvC	InvC
AI1	-0.0027*** (0.00)	-0.0029*** (0.00)	-0.0025*** (0.00)	-0.0025*** (0.00)	-0.0026*** (0.00)
Size	-0.0007** (0.00)	-0.0001 (0.00)	-0.0008*** (0.00)	-0.0010*** (0.00)	-0.0007** (0.00)
Lev	-0.0096*** (0.00)	-0.0093*** (0.00)	-0.0093*** (0.00)	-0.0087*** (0.00)	-0.0094*** (0.00)
ROA	0.0072 (0.00)	-0.0019 (0.01)	0.0050 (0.00)	0.0115** (0.00)	0.0071 (0.01)
TobinQ	0.0012*** (0.00)	0.0019*** (0.00)	0.0012*** (0.00)	0.0009*** (0.00)	0.0012*** (0.00)
FirmAge	-0.0031*** (0.00)	-0.0015 (0.00)	-0.0029*** (0.00)	-0.0037*** (0.00)	-0.0032*** (0.00)
Top1			0.0075*** (0.00)		
Board			0.0001 (0.00)		
_cons	0.0766***	0.0592***	0.0748***	0.0825***	0.0759***

Table 3. (continued)

	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
<i>N</i>	23145	19601	23144	23145	23145
<i>R</i> ²	0.015	0.017	0.016	0.031	0.016
adj. <i>R</i> ²	0.014	0.016	0.015	0.029	0.015
year	yes	yes	yes	yes	yes

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

5.4. Heterogeneity analysis

As shown in the heterogeneity analysis results in Table 4, this paper will further investigate how AI affects InvC among different types of enterprises. Column (1) has a coefficient of -0.0029 for high-tech industries and is at the 1% level of significance; column (2) does not differ significantly for non-high-tech industries. High-tech industries have good technological absorption capabilities, can easily be integrated with AI in their innovation activities, and can achieve various benefits; non-high-tech industries have weak digital foundations and are not suitable for rapid transformation by AI applications. Column (3) is not significant for heavily polluting enterprises, but column (4) is -0.0044 and significant at the 1% level for non-heavily polluting enterprises. High-polluting enterprises are subject to stricter environmental regulations and have thus invested in AI mainly for pollution control; non-polluting enterprises can use AI to improve their processes and products to avoid competition with the high-polluting enterprises. Column (5) is -0.0045 and significant at the 1% level for technology-intensive enterprises; columns (6) and (7) have insignificant coefficients for asset-intensive and labour-intensive enterprises. Technology-intensive enterprises can make full use of the good digital environment to introduce artificial intelligence in their main production process and improve efficiency; at the same time, low-end enterprises have not invested sufficiently in AI and remain at a disadvantage in competition due to their capital- and labour-intensive structures, so the substitution effect has not been fully realised. Based on the above results, the inhibitory effect of AI on involutionary competition is mainly manifested in non-heavily polluting and technology-intensive enterprises, and this marginal effect is significantly larger for these two groups than for the subgroup of high-tech industries. The above heterogeneous results show that the relationship between AI and market competition is very complex, so we need to focus on AI empowerment and targeted policies to improve the health of enterprises.

Table 4. Heterogeneity test analysis table

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	InvC	InvC	InvC	InvC	InvC	InvC	InvC
AI1	-0.0029*** (0.00)	0.0012 (0.00)	0.0004 (0.00)	-0.0044*** (0.00)	-0.0045*** (0.00)	-0.0005 (0.00)	0.0010 (0.00)
Size	-0.0007** (0.00)	-0.0001 (0.00)	-0.0005 (0.00)	-0.0008** (0.00)	-0.0006 (0.00)	0.0004 (0.00)	-0.0019*** (0.00)
Lev	-0.0117*** (0.00)	-0.0021 (0.00)	0.0166*** (0.00)	-0.0178*** (0.00)	-0.0186*** (0.00)	0.0187*** (0.00)	-0.0072* (0.00)
ROA	0.0070 (0.01)	-0.0004 (0.01)	0.0358*** (0.01)	0.0023 (0.01)	0.0028 (0.01)	0.0310** (0.01)	0.0207** (0.01)

Table 4. (continued)

TobinQ	0.0013*** (0.00)	0.0010* (0.00)	-0.0003 (0.00)	0.0009*** (0.00)	0.0012*** (0.00)	0.0007 (0.00)	0.0001 (0.00)
FirmAge	-0.0024** (0.00)	-0.0062** (0.00)	-0.0081*** (0.00)	-0.0010 (0.00)	-0.0009 (0.00)	-0.0057** (0.00)	-0.0067*** (0.00)
_cons	0.0742*** (0.01)	0.0704*** (0.02)	0.0682*** (0.01)	0.0795*** (0.01)	0.0712*** (0.01)	0.0439*** (0.02)	0.1117*** (0.01)
N	18440	4705	6425	16720	13862	4425	4809
R ²	0.018	0.012	0.016	0.031	0.033	0.022	0.015
adj. R ²	0.017	0.008	0.013	0.030	0.032	0.018	0.011
year	yes	yes	yes	yes	yes	yes	yes

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

6. Conclusion and recommendations

Based on the data of China's A-share listed companies, this paper will empirically investigate the effect of artificial intelligence application on the "involutionary" competition of these enterprises. Based on the above results, it can be concluded that AI technology has reduced intra-industry competition among enterprises. AI will improve the use of resources, strengthen the dissemination of knowledge in the supply chain, and restore the market's signalling function. The damping effect is relatively strong for non-heavy-polluting, technology-intensive enterprises, but it does not apply to heavy-polluting, asset-intensive or labour-intensive enterprises.

Based on the above analysis, this paper puts forward the following recommendations. First, the enterprise should no longer blindly pursue the wave of new technologies and begin to use artificial intelligence in different ways. Technology-intensive enterprises should increase the integration of artificial intelligence in their research and development and supply chain management to benefit from knowledge spillovers and technological differentiation, avoid homogeneous competition, etc. Asset-intensive and labour-intensive enterprises should first build a digital foundation in line with their own circumstances and then introduce intelligent tools; thus, they can avoid misallocation of resources due to excessive investment in technology. Second, the government should put AI policies in the top-level design of competition administration. Increase the speed of construction for the integrated data market to reduce institutional costs of digitalisation and explore synergy between AI and environmental or industrial policies in sectors with weak effects, such as heavy-polluting industries. At the same time, they should also use the knowledge spillover of leading chain companies to spread technical standards and management practices in the supply chain via industry-academia-research platforms and improve AI-enabled competition governance.

In the future, we will study the impact of external policy shocks on causality, observe changes in hyper-competitive behaviour induced by artificial intelligence over an extended period, and provide stronger support for the technology-market order hypothesis.

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