Proceedings of ICFTBA 2025 Symposium: Data-Driven Decision Making in Business and Economics
DOI: 10.54254/2754-1169/2025.BL29363

Research on the Impact of Artificial Intelligence on Corporate Governance—A Case Study of Agency Costs

Xinyun Ye

University of Macau, Macau, China
xinyunye5@gmail.com

Abstract. This paper looks at how investing in artificial intelligence (AI) affects company agency costs. Using data from non-financial firms listed in Shanghai and Shenzhen A-shares in China between 2012 and 2024, it carries out a real-world study with a fixed-effects model. The results show that corporate AI investment significantly increases both Type I and Type II agency costs, specifically the management expense ratio between shareholders and management, and the proportion of other receivables between major stockholders and minority stockholders. This worsens the conflicts of interest between company owners and managers, and also between large owners and small owners. Based on these conclusions, this paper proposes that a corporate governance system adapted to AI investment should be improved, and enterprises should focus on enhancing investment efficiency and building transparency to ensure that AI investment truly serves sustainable development and long-term value enhancement of enterprises.

Keywords: Artificial Intelligence, Corporate Governance, Agency Costs

1. Introduction

Artificial intelligence technology has become a key force driving changes in corporate governance, and its data analysis and intelligent decision-making capabilities are reshaping traditional governance models. However, academic circles hold divergent views on the impact of AI on agency costs. Some studies argue that AI technology can optimize decision-making and reduce agency costs, while others suggest that the returns on AI investment are unclear and may lead to interest tunneling. Against this background, this paper will use an empirical model to test the actual effects of AI and explore its impact on corporate governance efficiency based on firm-level data.

2. Literature review

2.1. Literature review on Artificial Intelligence

Artificial Intelligence (AI) refers to intelligent behaviors exhibited by artificial systems, which can perceive the environment, learn, reason, and take actions to achieve specific goals [1]. Current AI studies aim to build systems that can handle thinking tasks, including understanding language, recognizing pictures, and making decisions.

DOI: 10.54254/2754-1169/2025.BL29363

The development of AI has gone through several key stages. Early research focused on exploring "neural networks". McCulloch and Pitts first proposed the artificial neuron model, laying the foundation for subsequent studies [2]. In the 1980s, the emergence of the backpropagation algorithm promoted the initial application of neural networks [3].

At the beginning of the 21st century, breakthroughs in "deep learning" technology significantly improved AI performance. The Convolutional Neural Network (CNN) proposed by LeCun et al. achieved results surpassing human levels in image recognition [4]. Deep learning enables efficient representation learning of complex data through multi-layer neural network structures.

In recent years, "Large Language Models (LLMs)" have become a new paradigm in the field of AI. The Transformer architecture proposed by Vaswani et al. laid the foundation for models such as GPT and BERT [5-7], which have demonstrated amazing generalization capabilities in natural language processing tasks [5].

2.2. Literature review on corporate agency costs

The theory of agency costs can be traced back to the pioneering research of Jensen and Meckling [8]. They were the first to clearly create a theory about agency costs, showing that when business owners (principals) and managers (agents) have different goals, three main types of agency costs appear: monitoring costs (money owners spend to watch managers' actions), bonding costs (money managers spend to promise they will protect owners' interests), and residual loss (value loss caused when managers' choices do not match owners' best interests).This theoretical framework provides a basis for subsequent research and clarifies the core components of agency costs.

In subsequent studies, scholars have adopted various metrics to measure agency costs. Type I agency costs mainly reflect interest conflicts between owners and management. Ang et al. proposed that the management expense ratio (the proportion of management expenses to operating income) is a core indicator for measuring such agency costs [9]. A higher management expense ratio indicates a greater possibility of management wasting corporate resources or being slack. The rationality of this indicator lies in that an increase in management expenses usually means an increase in management's expenditures on non-productive activities, thereby undermining shareholders' interests.

Type II agency costs stem from the problem of interest expropriation between major stockholders and minority stockholders. Studies by La Porta et al. emphasize that the degree of separation between cash flow rights and control rights is a key indicator for measuring such costs [10]. This divide can cause large shareholders to use their control power to take advantage of smaller shareholders through connected deals or other actions, which raises agency costs. In studies about agency costs (disputes between large and small shareholders), the share of other receivables compared to total assets is now a common and direct way to show large shareholders' tunneling actions. This indicator can directly reflect the severity of major shareholders' tunneling behavior. To sum up, the theory of agency costs and its measurement indicators have been extensively studied and applied in academic circles. From interest conflicts between owners and management to interest expropriation between major stockholders and minority stockholders, the measurement indicators of agency costs have been continuously enriched and improved. Future research can further explore the impact of different governance mechanisms on agency costs and how to reduce agency costs by optimizing corporate governance structures, thereby improving corporate value and shareholders' interests.

DOI: 10.54254/2754-1169/2025.BL29363

2.3. Impact and mechanism of AI on corporate agency costs

Some literatures point out that the application of AI technology can reduce corporate agency costs.

First, the automated processes brought by AI technology will promote cost savings. AI technology reduces manual intervention and lowers management costs through automated processes. For example, intelligent office systems can automatically complete document processing, data sorting, and other tasks, improving work efficiency and reducing reliance on manual labor. Chui, Manyika, & Woetzel pointed out that AI technology can reduce reliance on manual labor through automated processes, thereby lowering labor costs [11].

Second, AI technology improves the accuracy and efficiency of decision-making through data analysis and prediction models, reducing management errors. For example, machine learning algorithms can process large amounts of financial and operational data, identify potential risks and opportunities, and help management make more informed decisions. Kiron, Shockley, Kruschwitz, & Haydock conducted an empirical study on the application of AI in data analysis and decision support, finding that it can improve the accuracy and efficiency of decision-making through data analysis and prediction models [12].

Third, AI technology optimizes resource allocation and reduces management costs through data analysis and prediction models. For example, McAfee, Brynjolfsson, Davenport, Patil, & Kaak studied the application of AI in supply chain management through case analysis and found that it can optimize resource allocation and reduce management costs through data analysis and prediction models [13]. Westerman, Bonnet, & McAfee further explored the application of AI in financial management and found that it can reduce management expenses by optimizing fund management [14]. Technological progress, especially the application of AI technology, has significantly reduced agency costs through automated processes, data-driven decision-making, and intelligent resource allocation [14]. In terms of decision support, machine learning algorithms improve decision accuracy and reduce management errors by analyzing massive data and predicting risks and opportunities [12]. In terms of resource allocation, intelligent supply chain and fund management systems achieve dynamic optimization, reducing inventory and operational costs [14]. These technological advancements work together to effectively reduce management inefficiencies and decision biases in agency costs, creating higher value for enterprises.

Despite the high expectations for AI technology to reduce agency costs, other literatures point out that the huge, complex, and highly specialized investments generated in its research and application may themselves become a hotbed for inducing new agency problems or exacerbating existing conflicts, thereby potentially increasing corporate agency costs.

First, AI investment may trigger serious over-investment and "managerialism" issues. Since AI is currently the most popular technological trend, management may promote AI projects out of motives such as building a "business empire", enhancing personal reputation, or chasing market hotspots (i.e., managerialism), rather than purely maximizing corporate value [15]. This irrational investment impulse may lead enterprises to invest resources in AI projects that do not match their core capabilities or have vague or unrealistic return on investment (ROI), resulting in huge capital waste and residual loss [16]. Begenau et al.'s research on technology investment shows that management often has incentives to invest in cutting-edge technologies to demonstrate their leadership, even if the economic benefits of these investments have not been confirmed [17].

Second, the characteristics of AI projects exacerbate information asymmetry and increase monitoring costs. AI technology has highly professional and "black-box" characteristics, with long R&D cycles, high failure risks, and value that is difficult to measure immediately using traditional financial indicators. This makes it more difficult for external shareholders and boards of directors to

DOI: 10.54254/2754-1169/2025.BL29363

effectively evaluate the necessity of AI investment and the authenticity of progress, thereby widening the information gap with management [18]. To monitor these complex and professional investment activities, shareholders have to bear higher monitoring costs, which directly increases agency costs.

Third, AI investment may become a tool for management to conduct earnings management or cover up poor operations. High AI capitalization expenditures and R&D expenses can be used as accounting means to smooth profits [19]. Management may beautify financial statements by classifying regular operating expenses as more promising "AI investments", or explain poor financial performance in economic downturns in the name of "strategic AI investment", thereby misleading shareholders [20]. This is not only an agency problem but also directly damages information transparency.

Based on this, this paper proposes the following hypotheses:

H1: The level of AI investment is significantly positively correlated with Type I agency costs (conflicts between shareholders and management).

H2: The level of AI investment is significantly positively correlated with Type II agency costs (conflicts between major stockholders and minority stockholders).

Subsequent sections of this paper will verify the above hypotheses through empirical models.

3. Research design

3.1. Variable selection

3.1.1. Dependent variables

The dependent variable in this paper is agency cost (Agency_Cost). The theory of agency costs originates from the pioneering research of Jensen and Meckling [8], which focuses on costs arising from interest conflicts between principals and agents. Drawing on the classic research methods of Ang et al. and Jiang et al. [9,21], this paper comprehensively measures corporate agency costs from the following two dimensions:

Type I agency costs (Agency_Cost1): Reflecting interest conflicts between shareholders and management. The management expense ratio is used as the core indicator, i.e., the ratio of management expenses to total operating income. A higher ratio indicates more severe potential on-the-job consumption, inefficiency, or resource waste by management, leading to higher agency costs for shareholders.

Type II agency costs (Agency_Cost2): Reflecting interest conflicts between major owners and minority owners. The proportion of other receivables to total assets is used as the core indicator. A higher ratio usually means more severe "tunneling" behavior by major shareholders through non-operating fund occupation, which harms minority stockholders' interests and increases agency costs.

3.1.2. Independent variable

The independent variable in this paper is the level of AI investment (AI_Inv_Ratio). The measurement method is as follows: This paper aims to measure the intensity of corporate capital allocation in the field of AI. Drawing on research related to corporate investment structure, the ratio of corporate AI investment to total investment in the current period is used to measure the level of AI investment. Specifically, it is calculated as: AI_Inv_Ratio = (AI-related investment amount / total

DOI: 10.54254/2754-1169/2025.BL29363

investment in the current period) * 100. A higher ratio indicates that enterprises allocate more resources to AI technology, meaning a higher level of AI investment.

3.1.3. Control variables

To control other factors that may affect corporate agency costs, this paper introduces the following control variables:

Firm size (LnAsset): Calculated using the natural log of total assets at year-end. The size of a firm may influence its agency costs.Operating income growth rate (Growth): Calculated as (current operating income - previous operating income) divided by previous operating income. A company's growth can affect its agency costs.Return on assets (ROA): Determined by dividing net profit by the average total assets. Profitability can impact agency issues.Board size (LnBoard): Found by taking the natural log of the total number of board members. Board size represents an important feature of a company's governance system.Proportion of independent directors (Indep_Ratio): Calculated by dividing the number of independent directors by the total number of board members. This measures how independent the board of directors is.

3.2. Model construction

Based on agency cost theory and existing research, this paper constructs the following basic econometric model to test the impact of AI investment on agency costs:

$$Agency\_Costit = \alpha + \beta * AIInvestLevel\_w + \gamma X_{it} + \mu_i + \upsilon_t + \varepsilon_{it} \tag{1}$$

Where, i represents the enterprise, and t represents the year. The dependent variable Agency_Costit is the agency cost of the i-th enterprise in year t. This paper focuses on two types of agency problems: ManagementExpenseRate_w (management expense ratio) measures the agency cost between shareholders and management, and Ind_ratio1_w (proportion of other receivables) measures the agency cost between major stockholders and minority stockholders.

The core independent variable AIInvestLevel_w represents the AI investment level of the i-th enterprise in year t, measured by the proportion of AI investment to total investment. The coefficient β is the central focus of this study: if β is significantly negative, it indicates that AI investment helps to mitigate agency costs; conversely, if β is significantly positive, it suggests that AI investment may exacerbate agency problems.

The set of control variables Xit includes firm-level variables that may affect agency costs, specifically: firm size (LnAsset), operating income growth rate (OperatingRevenueGrowth_w), return on assets (ROA_w), board size (In_DirectorNumber_w), and proportion of independent directors (ind_ratio_w). The model also controls for firm fixed effects (μ_i) and year fixed effects (υ_i), and ε_{it} is the random error term.

3.3. Data source

This paper uses data from manufacturing listed companies in China's Shanghai and Shenzhen A-shares from 2012 to 2024 as the research sample, excluding samples that were ST, *ST, or in the financial industry in the current year, as well as samples with excessive missing or obviously unreasonable key indicators. Relevant data in this paper are mainly sourced from the CSMAR database. Table 1 shows the descriptive statistical results of the main variables in this paper.

DOI: 10.54254/2754-1169/2025.BL29363

Table 1. Descriptive statistics

VarName	Obs	Mean	SD	Min	Median	Max
ManagementExpenseRate_w	46514	0.088	0.074	0.008	0.068	0.468
ind_ratio1_w	46373	0.273	0.260	0.001	0.206	1.363
AIInvestLevel_w	46090	0.005	0.009	0.000	0.002	0.056
ln_assets_w	46717	22.226	1.336	19.797	22.012	26.449
OperatingRevenueGrowth_w	46534	0.338	0.902	-0.766	0.117	6.188
ROA_w	46514	58.248	39.602	6.417	49.531	242.558
ln_DirectorNumber_w	47293	2.105	0.199	1.609	2.197	2.639
ind_ratio_w	47293	0.378	0.053	0.333	0.364	0.571

4. Empirical results and analysis

4.1. Benchmark regression results

Table 2 reports the benchmark regression results of the impact of AI investment on the two types of agency costs. Columns (1) and (2) show the regression results of AI investment on the management expense ratio (ManagementExpenseRate_w) and the proportion of other receivables (ind_ratio1_w) without control variables, respectively; Columns (3) and (4) further introduce firm-level control variables based on Columns (1) and (2). Columns (2) and (4) show that the coefficients of AI investment (AIInvestLevel_w) are significant at the 1% and 10% significance levels, respectively. This indicates that the higher the level of AI investment, the significantly higher the management expense ratio and the proportion of other receivables to total assets of enterprises. The above results verify the two research hypotheses proposed in this paper.

Table 2. Empirical regression results

	(1)	(2)	(3)	(4)
VARIABLES	ManagementExpenseRate_w	ManagementExpenseRate_w	ind_ratio1_w	ind_ratio1_w
AIInvestLevel_w	0.330***	0.368***	0.460	0.567*
	(0.109)	(0.0968)	(0.336)	(0.321)
ln_assets_w		-0.0268***		0.00743
		(0.00153)		(0.00474)
OperatingRevenueGrowth_w		-0.00257***		0.00593***
		(0.000568)		(0.00195)
ROA_w		-0.000903***		-0.00194***
		(3.36e-05)		(8.31e-05)
ln_DirectorNumber_w		0.00352		-0.00605
		(0.00471)		(0.0154)

DOI: 10.54254/2754-1169/2025.BL29363

ind_ratio_w		0.0133		-0.0300
		(0.0130)		(0.0408)
Constant	0.0860***	0.723***	0.275***	0.244**
	(0.000531)	(0.0373)	(0.00165)	(0.114)
Observations	41,532	41,384	41,421	41,280
R-squared	0.678	0.737	0.782	0.800
Firm Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes

Robust standard errors in parentheses

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

5. Conclusion

Using data from non-financial companies listed in Shanghai and Shenzhen A-shares in China between 2012 and 2024, this study applies a fixed-effects model to explore how AI investment affects corporate agency costs. The findings reveal that AI investment clearly increases two kinds of agency costs, deepening the conflicts of interest between owners and managers, and major stockholders and minority stockholders. Based on these results, the following policy suggestions are offered:

First, the corporate governance system adapted to AI investment should be improved. The government should formulate corporate governance guidelines for AI applications, clarify the responsible subjects for AI investment decision-making, application, and supervision, standardize the mechanisms for fund use and information disclosure, and prevent agency risks brought by technology application. At the same time, supervision and review of major shareholders' fund occupation and abnormal management expense expenditures should be strengthened to restrain short-term opportunistic behaviors that may be induced by AI investment.

Second, profitable enterprises should focus on improving the efficiency and transparency of AI investment. They should improve fund management systems, strengthen internal audits of the implementation of AI project budgets and resource usage, and eliminate improper related transactions and interest tunneling in the name of technology investment. Enterprises are encouraged to actively disclose the effectiveness of AI investment to enhance investors' confidence and reduce external financing costs and agency risks.

References

[1] Russell, S., & Norvig, P. (2020). *Artificial intelligence: A modern approach* (4th ed.). Pearson.
[2] McCulloch, W. S., & Pitts, W. (1943). A logical calculus of the ideas immanent in nervous activity. Bulletin of Mathematical Biophysics, 5, 115–133.
[3] Rumelhart, D. E., Hinton, G. E., & Williams, R. J. (1986). Learning representations by back-propagating errors. Nature, 323(6088), 533–536. https: //doi.org/10.1038/323533a0
[4] LeCun, Y., Bengio, Y. & Hinton, G. Deep learning. Nature 521, 436–444 (2015). https: //doi.org/10.1038/nature14539
[5] Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., Kaiser, L., & Polosukhin, I. (2017). Attention is all you need. *Advances in Neural Information Processing Systems, 30*, 5998-6008.

DOI: 10.54254/2754-1169/2025.BL29363

[6] Radford, A., Narasimhan, K., Salimans, T., & Sutskever, I. (2018). Improving language understanding by generative pre-training. OpenAI. https: //cdn.openai.com/research-covers/language-unsupervised/language_understanding_paper.pdf
[7] Devlin, J., Chang, M.-W., Lee, K., & Toutanova, K. (2019). BERT: Pre-training of deep bidirectional transformers for language understanding. Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers), 4171–4186.
[8] Jensen, M. C., & Meckling, W. H. (1976). Theory of the firm: Managerial behavior, agency costs and ownership structure. *Journal of Financial Economics, 3*(4), 305-360. https: //doi.org/10.1016/0304-405X(76)90026-X
[9] Ang, J. S., Cole, R. A., & Lin, J. W. (2000). Agency costs and ownership structure. The Journal of Finance, *55*(1), 81–106.
[10] Johnson, S., La Porta, R., Lopez-de-Silanes, F., & Shleifer, A. (2000). Tunneling. American Economic Review, 90(2), 22-27.
[11] Chui, M., Manyika, J., & Woetzel, J. (2018). Notes from the AI frontier: Applications and value of deep learning. McKinsey Global Institute.
[12] Kiron, D., Shockley, R., Kruschwitz, N., & Haydock, M. (2017). Reshaping business with artificial intelligence: Closing the gap between ambition and action. MIT Sloan Management Review.
[13] McAfee, A., Brynjolfsson, E., Davenport, T. H., Patil, D., & Kaak, P. (2019). Artificial intelligence: The next digital frontier? McKinsey Global Institute.
[14] Westerman, G., Bonnet, D., & McAfee, A. (2018). Leading digital: Turning technology into business transformation. MIT Press.
[15] Alder, S. (2023). Artificial intelligence and managerial overconfidence (Working Paper No. 2023-154). Becker Friedman Institute for Economics at the University of Chicago. https: //bfi.uchicago.edu/working-paper/2023-154/
[16] Jensen, M. C. (1986). Agency costs of free cash flow, corporate finance, and takeovers. American Economic Review.
[17] Begenau, J., Farboodi, M., & Veldkamp, L. (2018). Big data in finance and the growth of large firms. Journal of Monetary Economics.
[18] Cao, S., Liu, J., & Liu, Y. (2023). How does corporate use of artificial intelligence affect audit fees? https: //doi.org/10.2139/ssrn.4582663
[19] Huang, J., Li, K., & Shi, W. (2024). Strategic disclosure of AI investment: A tool for impression management? https: //doi.org/10.2139/ssrn.4698031
[20] Zhao, Y., et al. (2021). Corporate innovation and executive perks: Evidence from China. Journal of Corporate Finance.
[21] Jiang, G., Lee, C. M. C., & Yue, H. (2010). Tunneling through intercorporate loans: The China experience. Journal of Financial Economics, *98*(1), 1–20.