Research on the Impact of Stock Market Returns on the System Stability of Artificial Intelligence Enterprises: A Complex Network Perspective

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Abstract. The Central Political Bureau meeting held in April 2023 emphasized the importance of focusing on the development of Artificial Intelligence (AI), fostering an innovative ecosystem, and mitigating industry risks. As AI deeply integrates with the financial industry, the capital market faces new opportunities and challenges. This paper constructs a correlation network of AI industry stocks and empirically tests the impact of stock market returns on the system stability of AI enterprises. The findings reveal that firstly, stock market returns significantly enhance the system stability of AI enterprises. Secondly, stock market returns increase network clustering, which in turn, enhances system stability. Thirdly, compared to other areas, the impact of stock market returns on the system stability of AI enterprises is more pronounced in the North China, East China, and South China. This paper unveils the mechanisms through which stock market returns influence AI enterprise system stability, providing policymakers with insights and recommendations to promote the healthy development of the AI industry and prevent financial risks.

Keywords: Stock Market Returns; System Stability; Network Clustering; Regional Heterogeneity.

1 Introduction

Since the dawn of the 21st century, a new round of technological revolution and industrial transformation has been reshaping the global innovation landscape and restructuring the global economic framework. The Central Political Bureau meeting in April 2023 explicitly emphasized the importance of focusing on the development of general Artificial Intelligence (AI), fostering an innovative ecosystem, and managing risks. As a focal point of the fourth technological revolution, artificial intelligence plays a crucial role in alleviating demographic aging pressures, facilitating industrial structural transformation, and addressing sustainable development challenges [1]. AI not only drives industrial development but also introduces new opportunities and challenges in the capital market. The abnormal fluctuations in China's AI sector in June 2023 and the decline in stock prices of leading AI companies like NVIDIA underscore the need for in-depth research into the systemic stability of AI enterprises. Therefore, exploring how stock market returns affect the system stability of AI enterprises is of great significance for promoting the healthy development of the AI industry and enhancing national economic stability.

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As a new engine of era development, a large number of AI enterprises have rapidly emerged as an undeniable and accelerating new productive force. However, due to its characteristics of high investment, high output, and high risk, the AI industry faces significant market volatility risks. The static and dynamic spillover effects between stock market returns and industry stocks are closely related [2]. Fan et al. integrated the correlations of financial institutions' stock returns, sentiments, and marginal expected gaps, which reflect changes in financial system risks, internet public sentiment, and the degree of risk contribution, respectively, and found that systemic risk contagion in China exhibits clustering effects [3]. Effective risk adjustment implies a better market understanding of the real value of AI enterprises, which can enhance system stability [4]. Although numerous studies have explored the role of artificial intelligence in financial stability, the impact of stock market returns on its own system stability has not yet received adequate attention.

Network entropy reflects financial market volatility and serves as a measure of system stability within the stock market. Employing the complex-entropy causality plane, Shannon-Fisher information plane, and Renyi-Tsallis entropy plane, studies have observed that the complex structural features of stock indices vary with scale [5]. Zhu and Wei utilized the visible graph method to construct networks, analyzing changes in network structure using structural entropy of stock correlation networks [6]. They discovered that during economic crises, fluctuations in structural entropy are more pronounced, significantly affecting the system stability of stock correlation networks. Research on network visualization and hierarchical structures is crucial for understanding complex systems like financial markets. The global stock market turbulence triggered by the COVID-19 pandemic, including trading halts in the US market and significant declines in European stocks, has spurred researchers to delve deeper into the exploration of stock correlation networks [7]. Earlier studies using clustering coefficients, characteristic path lengths, and degree distributions to measure the topological properties of stock market networks found that these networks might exhibit small-world effects or scale-free properties [8]. Few scholars have analyzed the impact of stock market returns on the system stability of AI enterprises from a network perspective.

To explore how stock market returns influence the stability of AI enterprises, this paper selects quarterly data from 275 listed AI companies from 2018 to 2022, constructing a stock correlation network for the AI sector to study the impact of stock market returns on system stability. Compared to existing literature, this paper's marginal contributions are significant. Firstly, it uses network entropy to portray system stability, offering a new method and tool for assessing the stability of enterprise systems. Secondly, it examines how stock market returns affect system stability by influencing network structure, providing new theoretical support for understanding the mechanisms through which stock market returns impact system stability. Thirdly, it divides the 275 listed companies into seven regions, focusing on the heterogeneous characteristics of different regions in the process by which stock market returns influence enterprise stability, which has practical implications for region-specific policies.

The structure of this paper is as follows. Section 2 will conduct theoretical analysis and research hypotheses; Section 3 will introduce the empirical research design, including the construction of the stock correlation network model, the benchmark regression model, and the sources and descriptive statistics of the data; Section 4 will analyze empirical results, including benchmark regression and robustness analysis; Section 5 will further analyze mechanisms and heterogeneity; Section 6 will summarize the findings and offer policy recommendations.

2 Theoretical Analysis and Research Hypotheses

Based on the theories of efficient markets and behavioral finance, stock market prices absorb and reflect all available information, with high returns typically reflecting positive market assessments of stocks. In the technology-driven field of artificial intelligence, efficient information response and positive market expectations can enhance overall system stability [9]. Theories of financial market volatility suggest that tech stocks, due to their higher costs and the market's uncertainty about future expectations, are often considered riskier investments and tend to exhibit greater volatility than the overall stock market [10]. Based on this, the paper proposes Hypothesis 1:

H1: Stock market returns have a positive impact on the system stability of AI enterprises within the stock correlation network.

According to complex network theory, the clustering coefficient measures the degree of interaction between a particular stock and other stocks, with stock returns being significantly influenced by their position within the network. Significant correlations exist between certain stock price jumps, causing fluctuations in the prices of adjacent stocks within the same network [11]. Market microstructure theory focuses on the influence of market participant behavior on market prices and stability. High clustering reflects consistency among market participants in their information and trading strategies, which can positively affect system stability when stock market returns are high [12]. Based on this, the paper proposes Hypothesis 2:

H2: Stock market returns positively influence the system stability of AI enterprises by increasing network clustering.

External economic theories highlight the importance of domestic competition and geographic industry concentration in creating dynamic clusters. Being in a dominant position is beneficial for stimulating investment activity and improving stock market returns. Resource dependence theory suggests that organizations, to operate effectively and gain competitive advantages, rely on external resources. For high-tech industries, enterprises can improve the efficiency of technological innovation and enhance system stability through geographical advantages and the clustering effect [13]. Based on this, the paper proposes Hypothesis 3:

H3: There is regional heterogeneity in the process through which stock market returns affect the system stability of AI enterprises.

3 Empirical Research Design

3.1 Stock Correlation Network Model

In the stock network, nodes represent individual stocks and edges represent the correlation in price fluctuations between two stocks. Let N represent the number of stocks, T the period of study, Δt the time span between two adjacent stock networks, and denotes the length of the price time series used to construct a stock network. Using the sample data from day $[1,\tau]$, the first stock network is constructed where the daily return series of stocks i and j are $Y_i(1)$ and $Y_j(1)(i,j=1,2\ldots,N)$ respectively, constructing $M=INT[(T+\Delta t-\tau)/\Delta t]$ stock networks (where X denotes the integer part of $INT(X)$) .The m network is denoted as $G^m(V,E), m=1,2,\ldots,M$, and the correlation coefficient of stock prices in m network is given by Eq(1).

$$\rho_{ij}(m)=\frac{\langle Y_i(m)Y_j(m)\rangle-\langle Y_I(m)Y_j(m)\rangle}{\sqrt{(\langle Y_i^2(m)\rangle-\langle Y_i(m)\rangle^2)(\langle Y_j^2(m)\rangle-\langle Y_j(m)\rangle^2)}} \tag{1}$$

where $\langle Y\rangle$ denotes the Y mathematical expectation. The return series are calculated using logarithmic method from closing prices, $p_i^t(m)$ it represents the closing price of stock i on day t like Eq(2).

$$Y_i^t(m)=ln\,p_i^t(m)-ln\,p_i^{t-1}(m) \tag{2}$$

$\rho_{ij}(m)$ is transformed into a corresponding distance metric $d_{ij}(m)$; further transformations are applied to construct m stock networks reflecting the complex price fluctuation correlation patterns $G^m(V,E)$ of N stocks from day $1+(m-1)\Delta t$ to day $(m-1)\Delta t+\tau$ like Eq(3) and Eq(4)

$$d_{ij}(m)=\sqrt{2(1-\rho_{ij}(m))} \tag{3}$$

$$w_{ij}(m)=exp(-d_{ij}(m)), w_{ij}(m)\in[1/e^2,1] \tag{4}$$

Network topology features include the clustering coefficient and average path length. Drawing on prior research [14], the clustering coefficient for weighted networks are constructed as Eq(5):

$$C_{it}=\frac{1}{N}\sum_{i=1}^{N}\left(\frac{\sum_{j,k} w_{ij}w_{jk}w_{ki}}{\max_j(w_{ij})\sum_{j,k} w_{ij}w_{ki}}\right) \tag{5}$$

Network entropy describes the level of system stability, where higher network entropy indicates stronger stability of the stock correlation network system. Following the method used by Demetrius and Manke [15], a random matrix is obtained through the following formula Eq(6):

$$p_{ij}(m)=\frac{w_{ij}(m)}{\sum_{j=1}^{N} w_{ij}(m)} \tag{6}$$

Random matrix $p_{ij}(m)$ i row can serve as a transition probability distribution. Using Tsallis entropy formula, the Tsallis entropy HTT_{it} of a firm i in the stock network m, as Eq(7):

$$HTT_i(m) = (\frac{1}{\beta-1}(1-\sum_{j=1}^{N} p_{ij}^{\beta}(k))) \tag{7}$$

3.2 Benchmark Regression Model

This paper aims to explore the volatility characteristics of stock market returns and their intrinsic connection with enterprise system stability, analyzing how stock market returns impact the system stability of enterprises. The following benchmark regression model is constructed as Eq(8):

$$HTT_{it} = \alpha_0 + \alpha_1 ROA_{it} + \alpha_2 X_{it} + \gamma_i + \varepsilon_{it} \tag{8}$$

where i represents a listed enterprise, t represents a specific period measured in quarters, covering a total of 20 periods from 2018 to 2022. The dependent variable HTT_{it} denotes the system stability level of enterprise i during period t, as calculated previously. The explanatory variable ROA_{it} it represents the stock return of enterprise i in period t, X_{it} represents control variables at the enterprise level, γ_i represents individual enterprise effects, and ε_{it} is the random error term. In terms of selecting control variables that may affect system stability, this paper draws on the methodologies of Liu et al., Singhal et al., Alfaro et al., and Jiang et al. [14][16][17][18] combined with the availability of data, primarily selecting the following control variables; Enterprise asset size ($Size$) is represented by the natural logarithm of total assets; Level ratio (Lev) is calculated as total liabilities at year-end divided by total assets; Tax burden (IT/TP) reflects the tax burden on the enterprise; Cash flow to sales (CF/OI) measures the cash flow generated per unit of sales revenue; Current ratio (Liq) is the ratio of current assets to current liabilities; Total asset turnover (TTC) reflects the efficiency of asset utilization; Z-score (Z) measures the bankruptcy risk of the enterprise; Operating profit to total revenue ($EARN$) reflects the profitability of the enterprise.

3.3 Data Sources and Descriptive Statistics

The empirical study is based on 616 AI industry (iFinD concept) stock companies listed up to the end of 2022, sourced from the iFinD database. Companies that were treated as ST (special treatment due to financial issues) or had significant data omissions were excluded, retaining 275 companies. The study period spans from 2018 to 2022, with empirical analysis conducted quarterly. Company-related data were obtained from the Wind database and iFinD database. Descriptive statistics for each variable are reported in Table 1.

Table 1. Descriptive Statistics

Variables	Observations	Mean	Std.	Min	Max
HTT_{it}	5,500	187.126	0.054	186.791	187.229

ROA	5,500	2.391	4.941	-37.907	43.233
Size	5,500	22.716	1.000	20.781	27.067
IT / TP	5,500	9.519	97.521	-3948.142	3491.666
CF / OI	5,500	8.683	16.452	-264.069	131.889
TTC	5,500	0.574	0.333	0.046	2.842
Lev	5,500	38.216	18.214	2.265	119.268
Liq	5,500	2.631	2.335	0.430	31.403
Z	5,500	6.860	8.015	-2.350	149.699
EARN	5,500	4.913	23.994	-303.251	214.617

4 Analysis of Empirical Results

4.1 Benchmark Regression Analysis

Referencing the model setup discussed earlier, the results of the benchmark regression are presented in Table 2. Columns (1) and (2) feature the random effects model, while columns (3) and (4) utilize the fixed effects model. The inclusion of control variables in both the random and fixed effects models increases the goodness of fit, validating the effectiveness of incorporating these variables. The significance of the coefficient estimates is consistent across both models, with no substantial differences in the specific values. Based on Hausman tests and analysis of goodness of fit, this paper opts for the fixed effects model.

Column (3) displays the regression results without control variables. Comparing it to column (4), where control variables are included, there is a significant improvement in model fit, further verifying the appropriateness of including control variables. Moreover, the coefficients in both cases are significantly positive at the 99% confidence level. This confirms that stock market returns can enhance the system stability of enterprises within the AI stock correlation network, thus validating H1.

Table 2. Benchmark Regression Results

	HTT (1)	*HTT* (2)	*HTT* (3)	*HTT* (4)
ROA	0.002***	0.002***	0.001***	0.001***
	(0.000)	(0.001)	(0.000)	(0.000)
Size		-0.000		0.022***
		(0.002)		(0.004)
Lev		0.000***		0.000
		(0.000)		(0.000)
IT / TP		0.000		0.000
		(0.000)		(0.000)
CF / OI		-0.000		-0.000
		(0.000)		(0.000)
TTC		0.004		0.002
		(0.002)		(0.008)
Liq		-0.003		-0.003***
		(0.001)		(0.001)

Z		0.002***		0.001***
		(0.000)		(0.000)
$EARN$		-0.000		-0.000
		(0.000)		(0.374)
$Cons$	187.122***	187.100***	187.123***	186.623***
	(0.005)	(0.037)	(0.000)	(0.080)
Individual Fixed	YES	YES	YES	YES
N	5,500	5,500	5,500	5,500
R^2	0.025	0.049	0.015	0.061

(Note: Parentheses indicate robust standard errors; *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.)

4.2 Robustness Analysis

This paper conducted robustness tests by adjusting the parameters of the Tsallis entropy (HTT_{it}) specifications β to 0.5 and 1.5, respectively. The data for these tests were derived using the previously mentioned formulas, and the regression results are displayed in Table 3. Columns (1) and (2) present the regression outcomes without control variables and with control variables for a centrality parameter of $\beta = 0.5$. Columns (3) and (4) show the results without control variables and with control variables for a centrality parameter of $\beta = 1.5$. After substituting the dependent variable, the coefficient of ROA remains significant at the 99% confidence level under both parameter settings. This significant consistency underlines the robustness of the benchmark regression results and further corroborates H1.

Table 3. Robustness Analysis Results

	$HTT(0.5)$	$HTT(0.5)$	$HTT(1.5)$	$HTT(1.5)$
	(1)	(2)	(3)	(4)
ROA	0.000***	0.001***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.001)
Controls	NO	YES	NO	YES
Individual Fixed	YES	YES	YES	YES
N	5,500	5,500	5,500	5,500
R^2	0.007	0.015	0.009	0.028

(Note: Parentheses indicate robust standard errors; *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.)

5 Further Analysis

5.1 Mechanism Analysis

This paper employs the clustering coefficient as a mediating variable to examine the mechanism through which stock market returns influence the system stability of artificial intelligence stock correlation networks. Drawing on the two-step approach used by Semrau and Sigmund [19], the following mediation effect models are constructed as Eq(9) and Eq(10):

$$C_{it} = \beta_0 + \beta_1 ROA_{it} + \beta_2 X_{it} + \gamma_i + \varepsilon_{it} \tag{9}$$

$$HTT_{it} = \mu_0 + \mu_1 C_{it} + \mu_2 X_{it} + \gamma_i + \varepsilon_{it} \tag{10}$$

where in equations (10) and (11) represents the clustering coefficient of the listed enterprise (stock) i in period t. The focus is on the significance of the coefficients β_1 and when both are significant, it indicates a positive mediating effect. As shown in Table 4, at a 1% significance level, stock market returns have a positive effect on the clustering coefficient, and the clustering coefficient positively influences system stability. This suggests that stock market returns enhance system stability of AI enterprises by increasing network clustering.

In a highly clustered interconnected networks, stocks are no longer isolated entities but nodes in a network, forming dense connections with other stocks. These connections represent the flow of information, capital, and risk propagation pathways among stocks. When network clustering is enhanced, the links between stocks become tighter, allowing even minor fluctuations in any stock to rapidly propagate through the network. Due to these tight connections, risks in a highly clustered network can spread more quickly. Risk can be dispersed across the entire network. This risk dispersion effect helps to reduce the contribution of a single stock to the overall risk of the enterprise's investment portfolio, thereby enhancing the system stability of the enterprise. Thus, H2 is validated.

Table 4. Mechanism Analysis Results

	C_{it}	HTT_{it}
	(1)	(2)
ROA	0.000***	
	(0.000)	
$C_{i,t}$		0.061***
		(0.017)
Controls	YES	YES
Individual Fixed	YES	YES
N	5,500	5,500
R^2	0.064	0.044

(Note: Parentheses indicate robust standard errors; *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.)

5.2 Heterogeneity Analysis

The economic development levels vary significantly across different regions in China, and the distribution of AI enterprises is also uneven. This section explores the impact of regional disparities on system stability among AI enterprises. Based on China's geographical divisions, the country's provincial-level administrative regions are categorized into seven areas: Northeast, East China, North China, Central China, South China, Southwest, and Northwest. The data set includes 275 AI enterprises classified according to the aforementioned regional standards. The enterprises were then analyzed to determine regional heterogeneity, as shown in Table 5. The columns represent the following regions. (1) Northeast, (2) East China, (3) North China, (4) Central China, (5) South China, (6) Southwest, (7) Northwest.

In this paper, the coefficients ROA for the Northeast, Central China, Southwest, and Northwest regions are not significant. In contrast, the ROA coefficient for East China and North China is significant at the 90% confidence level in column (2) and (3) respectively. The ROA coefficient for South China is significant at the 95% confidence level in column (5). Specifically, AI enterprises in the Northeast, Central China, Southwest, and Northwest regions suffer from limitations due to infrastructure development and the maturity of the market environment. AI enterprises in these regions often occupy more peripheral positions in the network structure. Combined with insufficient policy support and incentive mechanisms, these areas have fewer AI enterprises, and the clustering effect is not pronounced. In contrast, AI enterprises in East China, North China, and South China exhibit distinct regional characteristics. Benefiting from their geographical advantages, these regions have successfully attracted a substantial amount of talent and technological resources, forming close inter-enterprise connections. These connections not only facilitate rapid information and capital flows but also significantly enhance system stability by increasing the network clustering.

Table 5. Heterogeneity Analysis Results

	HIT_{it}	HIT_{it}	HIT_{it}	HIT_{it}	HIT_{it}	HIT_{it}	HIT_{it}
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ROA	-0.000	0.001***	0.000*	0.002	0.001**	0.000	0.001
	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)	(0.001)
Controls	YES	YES	YES	YES	YES	YES	YES
Individual Fixed	YES	YES	YES	YES	YES	YES	YES
N	160	1,860	1,260	280	1,260	380	100
R^2	0.079	0.064	0.074	0.049	0.048	0.095	0.160

(Note: Parentheses indicate robust standard errors; *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.)

6 Conclusions and Policy Recommendations

Based on theoretical analysis and using quarterly data from 2018 to 2022 for 275 listed AI enterprises, this paper constructs a correlation network for the AI stock and empirically tests the impact of stock market returns on system stability. It also examines the heterogeneity of this impact across different regions. The empirical findings reveal that. Firstly, stock market returns positively influence the system stability within the AI stock correlation network; secondly, stock market returns enhance system stability of AI enterprises by increasing network clustering; thirdly, the impact of stock market returns on the system stability of AI enterprises is more pronounced in the North China, East China, and South China regions compared to other areas. Therefore, this paper offers the following policy recommendations. Firstly, policymakers should strengthen disclosure standards and enhance market transparency and fairness to boost investor confidence and promote stable growth in stock market returns, thereby enhancing the system stability of AI enterprises within the stock correlation network. Secondly, governments should encourage AI enterprises to engage in strategic cooperation, information sharing, and technological exchange to enhance network clustering and improve the overall system stability of the AI stock correlation network. Thirdly, for regions with well-developed AI stock correlation network, further relax market access and enhance market dynamism. For regions where AI stock correlation network development is lagging, increase policy support to accelerate development. Moreover, strengthen inter-regional cooperation and exchange to achieve resource sharing and complementarity, thus promoting the enhancement of system stability among AI enterprises.

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