Journal of Accounting, Finance and Auditing Studies
https://www.acadlore.com/journals/JAFAS

Transmission Risk of Stock Price Fluctuations Among Industries in Complex Financial Networks

Weishi Wang[1*], Junzhe Ding[1], Yuechen Zhou[2]

[1] School of Management and Engineering, Capital University of Economics and Business, 100070 Beijing, China
[2] BFA Interaction Design, California College of the Arts, CA94107 San Francisco, USA

[*] Correspondence: Weishi Wang (22023210046@cueb.edu.cn)

Received: 01-16-2024 **Revised:** 03-11-2024 **Accepted:** 03-23-2024

Citation: Wang, W. S., Ding, J. Z., & Zhou, Y. C. (2024). Transmission risk of stock price fluctuations among industries in complex financial networks. *J. Account. Fin. Audit. Stud.*, *10*(1), 37-50. https://doi.org/10.56578/jafas100105.

Abstract: In recent years, many researchers have studied some complex phenomena in the world from a new angle, and the subject of complexity science was born. In the field of complexity research, the study of social economics is very common. Because of the characteristics of financial market and its position in social economy, it is very important in complexity research. Based on complex network theory and vector autoregressive model (VAR) study of the stock market fluctuation and discusses the conduction effect between stock volatility in the industry on the influence of the correlation of share price volatility, aims to better understand the operating mechanism of the stock market, the more effective controlling the market development direction, to promote the healthy development of China's financial markets. In this paper, the rise and fall of stocks in 11 industries in the CSI 300 industry index are selected as variables, and the data from January 1, 2024, to March 1, 2024, are selected as research samples. Granger test and vector autoregressive model are used to calculate the conduction benefits between different industries. The complex network is constructed with industry as node and stock conduction direction as edge. Based on the analysis, we can find that in the CSI 300 industry index, there are several industries as the influence center of volatility, and their stock price fluctuations will affect the market of related industries, thus affecting the whole body. Based on the market situation of related industries in recent years, the correlation of fluctuations of different stocks in the stock market can be explained, and the influence of industry factors on stock price fluctuations can be deeply explored.

Keywords: Stock price fluctuation; VAR model; Complex financial network; Financial risk; Conducting research

JEL Classification: C32; C58; C63; G01

1. Introduction

The current domestic and international dual circulation is an inevitable and crucial development pattern. The connections between industries in terms of trade, investment, technology, and production materials are becoming increasingly close. The interdependence between industries leads to the transmission of stock price fluctuations to adjacent industries. Compared with foreign financial markets, the current development of China's stock market sees many companies intentionally spreading false information for their own benefit. Investors' misjudgments of the trends in the financial market are influenced by this false data. Many individual investors exhibit blind trend-following and speculative behavior in their investments. In this situation of information asymmetry, it is easy for the party with the information advantage to control the direction of investment, leading to greater losses. In conclusion, investors may face limitations in understanding market conditions due to information constraints and subjective factors, as well as a lack of awareness of the transmission relationship between stock price fluctuations and industries. These factors naturally restrict the development of China's stock market. Therefore, for the sustainable development of China's stock market, it is necessary to understand the current internal situation of the stock market and the interdependent patterns of stock price fluctuations objectively and comprehensively in different industries, to reasonably control the direction of stock market development.

Furthermore, studying the volatility and spillover effects between industries in the stock market can lead to a more accurate prediction of market fluctuations. Investors, after understanding the transmission patterns between different industries, can adopt a more rational approach to market information to maximize gains.

With the development of the field of complexity science, more research tools have been provided for the field of socioeconomics. Utilizing complex network theory to study the transmission of stock price fluctuations can rely on stock market indices, which adequately reflect the state of the economic market. This approach not only helps to reduce the impact of financial risk by analyzing stock index fluctuations but also provides a certain degree of decision support for addressing potential risks in various industries.

Returns on different stocks in the stock market can have varying degrees of impact on each other, and different industries are also a factor influencing stock price fluctuations. Studying transmission can summarize the regularity of stock price fluctuations between industries and, under the premise of probing market risks as much as possible, further predict the direction of stock price fluctuations between industries.

In addition, it is also possible to explore the synchronicity of stock price fluctuations, also known as the "simultaneous rise and fall" phenomenon in China, wherein most stock prices rise or fall simultaneously during a certain period. This involves examining the inherent patterns and essence of this phenomenon. Lai & Hu (2021) constructed a complex network in which nodes represent countries and edges represent economic connections between countries, to measure and analyze the economic interconnectedness and influence among countries. They introduced linear Granger causality analysis to estimate the statistically significant relationships between different countries and further analyzed whether an increase in risk in one country would lead to an increase in risk in another country.

In recent years, foreign researchers have primarily utilized models like ARCH, particularly the GARCH family of models, to study stock market volatility. In conjunction with complex network theory, these researchers have utilized GARCH effects analysis of companies as nodes and used volatility spillover relationships as edge weights to construct a linked network. Additionally, Mylonidis & Kollias (2010) conducted a study on the linkage of the four major European stock markets using stationary tests and cointegration techniques, concluding that the stock markets of Germany and France demonstrated the highest degree of linkage. Nishimura et al. (2016) applied GARCH models to study the volatility spillover effects between the stock markets of China and Japan, finding that the Chinese stock market exhibits volatility spillover effects on the Japanese stock market, whereas the volatility of the Japanese stock market does not significantly affect the Chinese market, possibly due to measures taken by the Chinese stock market to restrict foreign investment. Gourène et al. (2019) conducted a study on the volatility spillover effects in stock markets of several countries including India, Russia, Brazil, France, Japan, the United States, the United Kingdom, and Germany, utilizing a VAR model and maximum overlap discrete wavelet transform (MODWT). Their conclusion suggested a significant connection between the choice of data for long-term or short-term stock market volatility and spillover effects (Gourène et al., 2019). Slim et al. (2017) also utilized VAR-GARCH models to study the risk value of global stock market indices, attempting to explore the influence paths of global stock market volatility.

Researchers in China have utilized various methods to study stock price volatility, including time series data models, impulse response functions, and Granger causality tests. For example, Sun & Yu (2020) proposed a two-stage financial time series volatility prediction method called the GARCH-SVR model, which combines the GARCH model and SVR (Support Vector Regression). This was aimed at improving the accuracy of financial time series volatility prediction (Sun & Yu, 2020). Rong et al. (2019) research delved into the price interaction and causal relationship between the domestic and international timber markets in China, revealing the complex dynamic relationship between the two markets in the short and long term. Advanced statistical methods such as Wald-Granger causality test, Geweke causality test, and spectral Granger causality test were utilized to conclude that there is a significant immediate feedback mechanism between the domestic and international timber markets and the sawn timber market, especially in the short term, where price fluctuations are easily transmitted between the two markets. Long-term prices, on the other hand, are mainly influenced by factors such as demand, resources, production capacity, and policies (Rong et al., 2019). Li et al. (2019) investigated the relationship between investor attention and crude oil prices through empirical analysis, using Google Search Volume Index (GSVI) to measure investor attention. The study analyzed major global crude oil markets, considering potential structural breaks and non-linear relationships, and utilized Fourier unit root test and non-linear Granger causality test (Li et al., 2019). Chen et al. (2022) used complex network modeling methods to identify the dynamic influence of financial institutions in the financial network based on Stock Comprehensive Evaluation (SCE). Zhang et al. (2019) constructed a multidimensional economic spatial model by defining economic measures and gravity spatial weight matrix, effectively capturing the complex interactions among financial. Xiao et al. (2023) proposed a new fractional integration to implement the GARCH model, aiming to improve the prediction of volatility in financial markets. By constructing weighted realized volatility and incorporating long memory parameters, the model can more accurately capture the long-term correlation of market volatility. This provides technical support and risk control strategies for investors and offers a scientific basis for financial market risk management (Xiao et al., 2023).

Kou et al. (2022) comprehensively reviewed the major advances in network resilience and financial network literature, and discussed key elements and applications of financial network resilience in financial regulation, including financial network information, network resilience measurement, financial regulatory technology, and regulatory applications. Hu et al. (2019) applied complex network methods to analyze the clustering effect of stock price jump risk in the Chinese stock market. Using CSI 300 index component stocks as samples, high-frequency data at 5-minute intervals and the MinRV method were utilized to extract jumps. A complex network of stock price jumps was constructed using the minimum spanning tree algorithm, revealing significant correlations among stocks in the entire jump network, with manufacturing stocks playing the most crucial role (Hu et al., 2019). In the study (Si et al., 2022), the main research focused on constructing a complex financial network equivalent to high-frequency data using low-frequency time series data, and proposed an improved compressive sensing method. Based on financial network information variables and genetic algorithms, Liu et al. (2019) proposed a method that combines network variables and GA-optimized Gradient Boosting Decision Tree (GBDT), referred to as FNI-GA-GBDT.

This study focuses on the interdependence of stock price fluctuations between industries, the direction of volatility spillovers, and the underlying reasons for stock price volatility. The research methods utilized include Granger causality tests and vector autoregressive models. Granger causality tests not only assess the correlation between stock price fluctuations in different industries but also indicate the direction of volatility transmission, thereby constructing a directed network of stock price volatility transmission. However, this model has its limitations: firstly, it lacks a scale of correlation for the direction of stock price volatility transmission obtained through Granger causality tests, resulting in an absence of edge weights in the network constructed based on this. Secondly, Granger causality tests primarily focus on the relationship before and after the occurrence of volatility from a mathematical and logical perspective, rather than representing a strict causal logical relationship, leading to some scholars questioning the applicability of the Granger causality network.

Building upon this, the study further constructs a vector autoregressive model to conduct impulse response analysis on the inter-industry stock price volatility, aiming to determine whether there is contagion interdependence between two industries. Through the analysis of impulse response graphs, the study also aims to assess the practical significance of the correlation between stock price volatility and industry.

2. Materials and Methods

2.1 Theory Related to Stock Price Fluctuations

The stock market is a place where issued stocks are traded, divided into exchange markets and over-the-counter markets. Contradictions of supply and demand are a significant focus in the process of social reproduction, as there is a significant amount of idle or unutilized capital in society. To stimulate consumption and promote the increase of capital value, it is necessary to find channels for circulation. Additionally, the development of the economy in our country requires more capital investment, creating the need for borrowing more funds. The idle and unutilized funds in other aspects of society provide this supply, giving rise to the stock market, which serves to address the supply and demand contradiction of social capital. The stock price index serves as a gauge of the overall stock market prices and the extent of fluctuations, reflecting the development of the national or regional economic market. It is used to indicate the changes in stock market conditions.

The development of the Chinese stock market has been extremely rapid in recent years, but it is currently facing the following issues:

Impact of the post-COVID-19 pandemic. The long-term impact of the COVID-19 pandemic on the global economy, particularly on the service industry, is expected to persist. From the perspective of macroeconomic development, the dual pressure of the pandemic and the economy has led to a certain level of market pessimism, which is one of the important reasons for the significant market decline.

New Cold War concerns brought about by the Russia-Ukraine conflict and the Israel-Palestine conflict. Russia's special military actions in Ukraine have led to comprehensive sanctions by the West against Russia, which have almost completely severed economic ties, including measures such as asset freezes or seizures, settlement suspensions, and trade suspensions. This has led investors to consider whether the United States will target Chinese concept stocks in the future, influencing to a certain extent the investment intentions of A-share market investors.

Restrictions of the listing system on private enterprises. China's stock market listing system follows a government approval process, which to some extent has an "administrative" influence on the standards for listing selection. This has led to more opportunities for listing financing being oriented towards large state-owned enterprises, thereby limiting the development environment for private enterprises.

The fundamental reason investors allocate funds to purchase stocks is to gain profits, hoping for stock price increases to generate returns. However, deviations in actual returns from anticipated returns can impact investors' behavior. To maximize returns, investors naturally seek the best investment options, considering factors affecting stock price fluctuations:

The reputation and operational status of the company issuing the stocks. A company with a strong reputation and high visibility within society generally has better operational conditions, leading to increased profits for investors. As a result, more people invest in the company's stocks, driving greater profits for the company, improving its operational status, and creating a positive cycle.

Global events and circumstances, including a country's economic market, policies, trade conditions, and bank interest rates, can significantly impact stock prices. For example, the gross domestic product (GDP) generally correlates positively with stock price fluctuations. Inflation can lead to significant and rapid stock price fluctuations due to rising prices. Additionally, stock prices are influenced by wars and their associated changes.

Investment preferences and their impact on the stock market. People generally prefer to invest in specific categories of stocks. Over time, regardless of price fluctuations, investors tend to continue buying the same type of stocks.

Blindly following investment trends. Some investors are easily influenced by significant market trading trends. Fearing missed opportunities for substantial profits, they choose investment options without considering their own circumstances, leading to market fluctuations.

Artificial manipulation and its impact on the stock market. Some individuals capitalize on informational advantages, making early purchases or sales of stocks to generate profits and influencing other investors to invest.

2.2 Granger Causality Test

Granger causality test is applied to two economic variables to determine whether there is a causal relationship between them. That is, for two economic variables *x* and *y*, if *x* is the cause variable of *y*, but *y* is not the cause variable of *x*, then the past values of *x* in the time series can predict the future development of *y*, while the past data of *y* does not significantly help predict the future development of *x*. Based on the time series shown in the graph below:

$$y_t = \gamma + \sum_{m=1}^{p} \alpha_m y_{t-m} + \sum_{m=1}^{p} \beta_m x_{t-m} + \varepsilon_t \tag{1}$$

The lag order "p" can be determined based on information criteria or sequential t-rules from large too small. Testing the null hypothesis H_0: $\beta_1 = \ldots = \beta_p = 0$. That is, past values of *x* do not effectively predict future values of *y*. If the null hypothesis is rejected, then it is said that *x* is a "Granger cause" of *y* (Rossi & Wang, 2019).

2.3 Vector Autoregressive Process

We first assume a bivariate VAR(*p*) model.

$$\begin{cases} y_{1t} = \beta_{10} + \beta_{11} y_{1,t-1} + \cdots + \beta_{1p} y_{1,t-p} + \gamma_{11} y_{1,t-1} + \cdots + \gamma_{1p} y_{1,t-p} + \varepsilon_{1t} \\ y_{2t} = \beta_{20} + \beta_{21} y_{1,t-1} + \cdots + \beta_{2p} y_{1,t-p} + \gamma_{21} y_{1,t-1} + \cdots + \gamma_{2p} y_{2,t-p} + \varepsilon_{2t} \end{cases} \tag{2}$$

where, $\{y_{1t}, y_{2t}\}$ are the dependent variables, in this study, they belong to time series in stock price volatility analysis. *p* is the lag order, acting as the explanatory variables of $\{y_{1t}, y_{2t}\}$. ε_{1t} and ε_{2t} do not have autocorrelation, but other disturbance variables in the equation may have contemporaneous correlation, i.e.

$$\operatorname{cov}(\varepsilon_{1t}, \varepsilon_{1t}) = \begin{cases} \sigma_{12}, t = s \\ 0, other \end{cases} \tag{3}$$

From this, we can organize and obtain:

$$\begin{pmatrix} y_{1t} \\ y_{2t} \end{pmatrix} = \begin{pmatrix} \beta_{10} \\ \beta_{20} \end{pmatrix} + \begin{pmatrix} \beta_{11} \\ \beta_{21} \end{pmatrix} y_{1,t-1} + \cdots \begin{pmatrix} \beta_{1p} \\ \beta_{2p} \end{pmatrix} y_{1,t-p} + \begin{pmatrix} \gamma_{11} \\ \gamma_{21} \end{pmatrix} y_{2,t-1} + \cdots \begin{pmatrix} \gamma_{1p} \\ \gamma_{2p} \end{pmatrix} y_{2,t-p} + \begin{pmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{pmatrix} \tag{4}$$

Combining the same lag order parameters, we obtain:

$$\begin{pmatrix} y_{1t} \\ y_{2t} \end{pmatrix} = \begin{pmatrix} \beta_{10} \\ \beta_{20} \end{pmatrix} + \begin{pmatrix} \beta_{11} & \gamma_{11} \\ \beta_{21} & \gamma_{21} \end{pmatrix} \begin{pmatrix} y_{1,t-1} \\ y_{2,t-1} \end{pmatrix} + \cdots + \begin{pmatrix} \beta_{1p} & \gamma_{1p} \\ \beta_{2p} & \gamma_{2p} \end{pmatrix} \begin{pmatrix} y_{1,t-p} \\ y_{2,t-p} \end{pmatrix} + \begin{pmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{pmatrix} \tag{5}$$

Set $y_t \equiv \begin{pmatrix} y_{1t} \\ y_{2t} \end{pmatrix}, \varepsilon_{1t} \equiv \begin{pmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{pmatrix}$ and by stipulating the corresponding coefficients, we can obtain:

$$y_t = \underbrace{\begin{pmatrix} \beta_{10} \\ \beta_{20} \end{pmatrix}}_{\Gamma_0} + \underbrace{\begin{pmatrix} \beta_{11} & \gamma_{11} \\ \beta_{21} & \gamma_{21} \end{pmatrix}}_{\Gamma_1} y_{t-1} + \cdots + \underbrace{\begin{pmatrix} \beta_{1p} & \gamma_{1p} \\ \beta_{2p} & \gamma_{2p} \end{pmatrix}}_{\Gamma_p} y_{1,t-p} + \varepsilon_t \tag{6}$$

Namely:

$$y_t = \Gamma_0 + \Gamma_1 y_{t-1} + \cdots + \Gamma_p y_{1,t-p} + \varepsilon_t \tag{7}$$

Because this model is like the AR(p) model, it is called VAR(p) (Bohannon et al., 2020).

2.4 Selection of Lag Order and Residual Testing

After estimating the covariance matrix and setting it as $\hat{\Sigma}$ with T as the sample size, the i and j elements of matrix $\hat{\Sigma}$ can be obtained:

$$\hat{\Sigma}_{ij} \equiv \frac{1}{T} \sum_{t=1}^{T} \hat{\varepsilon}_{it} \hat{\varepsilon}_{jt} \tag{8}$$

Once the (i, j) elements of the matrix are determined, we can then calculate AIC and BIC.

$$AIC(p) \equiv \ln \left| \hat{\Sigma} \right| + n(np+1)\frac{2}{T} \tag{9}$$

$$BIC(p) \equiv \ln \left| \hat{\Sigma} \right| + n(np+1)\frac{\ln T}{T} \tag{10}$$

n is the number of variables in the model, p is the lag order, and $n(np+1)$ is the total number of coefficients to be estimated within the system (Shahbaz et al., 2016).

When constructing a VAR model, it is necessary to test whether it belongs to a white noise process, i.e., to check for the presence of autocorrelation in the residual sequence. Assuming a VAR(p) model has been estimated as VAR($p-1$) model, when handling the disturbance variables, the last lagged term of the explanatory variables is also treated as a disturbance variable, resulting in the occurrence of autocorrelation, thus leading to different OLS estimates. This necessitates the reselection of the lag order.

2.5 The Stationary Application of VAR

In the VAR(p) model, if $\{\varepsilon_t\}$ is a white noise process, then for characteristic equation of a complex number z:

$$\left| I_n - \Gamma_1 z - \cdots \Gamma_p z^p \right| = 0 \tag{11}$$

All its solutions lie outside the unit circle formed by the complex number z in the complex plane. Therefore, it can be concluded that the VAR(p) is a stationary model. It should be noted that when all eigenvalues lie within the unit circle, it meets the stationarity property of VAR (1). Therefore, in general, the VAR(p) model can first be expressed in the form of VAR (1), and then its stationarity can be determined through eigenvalue calculations (Oravecz & Vandekerckhove, 2023).

2.6 Principle of VAR Pulse Response Function

To define the impulse response function of VAR, the vector moving average process needs to be characterized.

Extending the one-dimensional vector moving average process to the multidimensional case, it is denoted as:

$$y_t = \alpha + \psi_0 \varepsilon_t + \psi_1 \varepsilon_{t-1} + \psi_2 \varepsilon_{t-2} + \cdots = \alpha + \sum_{j=0}^{\infty} \psi_j \varepsilon_{t-j} \tag{12}$$

In the defined n-dimensional infinite-order vector moving average process, $\psi_0 = I_n$, ψ_j is an n-th order matrix. In addition, an infinite-lagged matrix polynomial can also be defined, so the n-dimensional infinite-order vector moving average process can be expressed as:

$$y_t = \alpha + \psi_0 \varepsilon_t + \psi_1 \varepsilon_{t-1} + \psi_2 \varepsilon_{t-2} + \cdots = \alpha + \sum_{i=0}^{\infty} \psi_i \varepsilon_{t-i} \tag{13}$$

According to the vector differential method, we can transform and obtain that $\frac{\partial y_{i+s}}{\partial \varepsilon_t} \Psi_s$, $\frac{\partial y_{t+s}}{\partial \varepsilon_t'}$ are the partial derivatives of n-dimensional row vector ∂y_{i+s} with respect to n-dimensional column vector ε_t'. Its mathematical significance is when the j-th parameter has an increase of one unit in the disturbance term ε_{jt} in period t while other disturbance terms and parameters are ignored, it measures the impact on the value of the i-th parameter in period ($t+1$). If we consider $\frac{\partial y_{i,t+s}}{\partial \varepsilon_{jt}}$ as a function of time change, this represents the impulse response function (IRF) (Usman, 2023).

3. Results

3.1 Data Selection

For industry segmentation, there are 11 sectors including real estate, materials, telecommunications, industrial, utilities, financials, optional, energy, consumer, information, and pharmaceuticals. The variable chosen is the stock price fluctuations of industry stocks included in the CSI 300 Index from January 1, 2024, to March 1, 2024, totaling 429 data points.

The reason for selecting the CSI 300 as the data sample is to conduct a study on the transmission of stock market volatility in China. The focus of the study naturally lies in industry factors, necessitating a detailed exploration of the interconnected relationships between different industries and their corresponding market backgrounds. Therefore, the data sample for industry classification needs to be specific and explicit. The CSI 300 Industry Index by CSI Limited offers a superior industry classification for stock market indices. It covers a larger number of listed companies and represents a more extensive spectrum of the economy.

The data is sourced from CSI Limited, and the statistical analysis software used is stata16.

3.2 Transmission of Stock Price Fluctuations in the Financial Industry Across Industries

3.2.1 Materials and finance industry

Since the premise of Granger causality test is that the sample data sequence is stationary, the unit root stationarity test is carried out on the data first. As shown in Table 1 and Table 2, the sample data sequences of the materials industry and the financial industry are both stationary.

Table 1. Industrial stability test

Dickey-Fuller Test for unit root			Number of obs =	38
			Interpolated Dickey-Fuller	
	Test Statistic	**1% Critical Value**	**5% Critical Value**	**10% Critical Value**
Z(t)	**-5.411**	**-4.260**	**-3.548**	**-3.209**

MacKinnon approximate p-value for Z(t) = **0.000**

Table 2. Financial stability test

Dickey-Fuller Test for unit root			Number of obs =	38
			Interpolated Dickey-Fuller	
	Test Statistic	**1% Critical Value**	**5% Critical Value**	**10% Critical Value**
Z(t)	**-5.300**	**-4.260**	**-3.548**	**-3.209**

MacKinnon approximate p-value for Z(t) = **0.000**

The method used in this paper is the Augmented Dickey-Fuller (ADF) unit root test, the formula for the test is:

$$\Delta y_t = \beta_0 + \delta y_{t-1} + \gamma_1 \Delta y_{t-1} + \cdots + \gamma_{p-1} \Delta y_{t-p+1} + \gamma t + \varepsilon \tag{14}$$

The original hypothesis and alternative hypothesis are: H_0: $\delta = 0$; H_1: $\delta < 0$

If the null hypothesis is accepted and the alternative hypothesis is rejected, it proves that the time series has a unit root and is non-stationary; conversely, if the series does not have a unit root, it is considered stationary. The ADF test in stata 17 is denoted as *Z*. The smaller the *Z* value, the more likely the null hypothesis is to be rejected, indicating that the series is stationary.

As shown in the Table 3, the series is stationary. To build a VAR model, it is necessary to select the optimal lag order. This study uses various criteria such as FPE, AIC, SBIC, HQIC, and LR tests to determine the optimal lag order of the model.

Table 3. Lag term order selection of materials and finance industry

Selection-order Criteria

Sample: **6-39** Number of obs = 34

Lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	**-114.733**				**3.29011**	**6.86664**	**6.89726**	**6.98643**
1	**-101.509**	**26.449**	**4**	**0.000**	**1.914***	**6.32403**	**6.41589**	**6.59339**
2	**-98.2092**	**6.5986**	**4**	**0.159**	**2.00129**	**6.36525**	**6.51835**	**6.81418**
3	**-97.2948**	**1.8289**	**4**	**0.767**	**2.418**	**6.54675**	**6.76109**	**7.17525**
4	**-89.3869**	**15.816***	**4**	**0.003**	**1.94828**	**6.31687**	**6.59245**	**7.12495**

Endogenous: d1y d1x

Exogenous: _cons

As shown in the Figure 1, the lag order of 1 is determined to be optimal based on the comprehensive evaluation of various criteria.

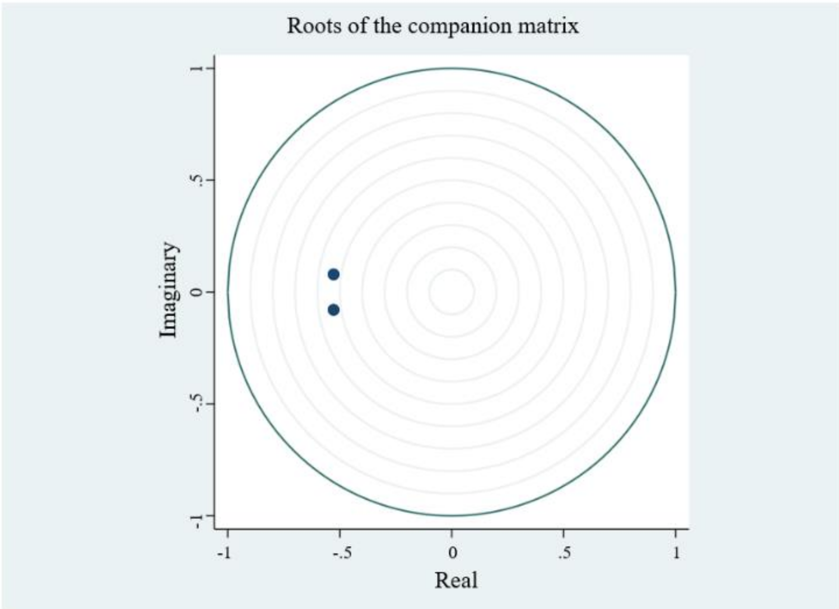

Figure 1. Materials and finance industries stability determination of VAR model

After determining the lag order and constructing the model, it is necessary to test the stability of the model. If the eigenvalues are inside the unit circle, it indicates that the model is stable. As shown in the Table 4, the model is stable.

Table 4. Materials and finance industry Granger causality test

Granger Causality Wald Tests				
Equation	**Excluded**	**chi2**	**df**	**Prob > chi2**
d1y	d1x	**.53274**	**1**	**0.465**
d1y	ALL	**.53274**	**1**	**0.465**
d1x	d1y	**.05828**	**1**	**0.809**
d1x	ALL	**.05828**	**1**	**0.809**

The specific steps required for constructing the model are as mentioned above. Granger causality tests were conducted on the data of two industries, and it was determined that there is no causal relationship. When conducting Granger causality analysis between the financial industry and the other 9 industries (excluding itself), it is found that the financial industry exhibits causal relationships with the optional consumer industry, the primary consumer industry, the information technology industry, and the pharmaceutical and health industry, among others. As the financial market is the lifeblood of the Chinese economy, its stock price fluctuations are closely related to the entire stock market. Therefore, this paper chooses to research the transmission direction and the real explanation of the transmission effect starting from the financial market. The specific exploration is described in the following sections, and the testing processes for other non-existent causal relationships are omitted.

3.2.2 Financial and optional consumer industry

The first step is to test the data for stationarity. As shown in Table 5 the conclusion is that optional consumer industry is stationary.

Table 5. Optional consumer industry stability test

Dickey-Fuller Test for unit root			Number of obs =	38
			Interpolated Dickey-Fuller	
	Test Statistic	**1% Critical Value**	**5% Critical Value**	**10% Critical Value**
Z(t)	**-6.503**	**-4.260**	**-3.548**	**-3.209**

MacKinnon approximate p-value for Z(t) = **0.000**

Using multiple judgment criteria such as FPE, AIC, SBIC, HQIC, and LR tests as shown in Table 6, the optimal lag order of the model is determined to be 2.

Table 6. Lag term order selection of financial and optional consumer industry

Selection-order Criteria

Sample: **6-39** Number of obs = 34

Lag	**LL**	**LR**	**df**	**p**	**FPE**	**AIC**	**HQIC**	**SBIC**
0	**-116.303**				**3.60846**	**6.959**	**6.89726**	**7.04879**
1	**-107.895**	**16.815**	**4**	**0.002**	**2.78679**	**6.69972**	**6.79158**	**6.96908**
2	**-100.016**	**15.76**	**4**	**0.003**	**2.22564**	**6.4715**	**6.6246***	**6.92043**
3	**-97.6839**	**4.6631**	**4**	**0.324**	**2.47399**	**6.56964**	**6.78398**	**7.19815**
4	**-96.1858**	**2.9964**	**4**	**0.558**	**2.9063**	**6.71681**	**6.99239**	**7.52488**

Endogenous: d1y d1x

Exogenous: _cons

According to the Granger causality test shown in Table 7, the stock price fluctuations in the financial industry have a causal effect on the optional consumer industry.

Table 7. Financial and optional consumer industry Granger causality test

Granger Causality Wald Tests				
Equation	**Excluded**	**chi2**	**df**	**Prob > chi2**
d1y	d1x	**6.5208**	**2**	**0.038**
d1y	ALL	**6.5208**	**2**	**0.038**
d1x	d1y	**3.6266**	**2**	**0.163**
d1x	ALL	**3.6266**	**2**	**0.163**

As shown in Figure 2, since there is a causal relationship, we further analyzed the impulse response functions of the two industries. The stock price fluctuations in the financial industry will have a negative impact on the optional consumer industry. As shown in the figure, when there is a fluctuation in the financial industry, it has a positive impact on the optional consumer industry, reaching its peak in the second period, followed by a diminishing negative impact, gradually turning negative, reaching its peak in the third period, and then alternating between positive and negative effects, before stabilizing after the sixth period. When there are fluctuations in the optional consumer industry, the impact on the financial industry is not significant.

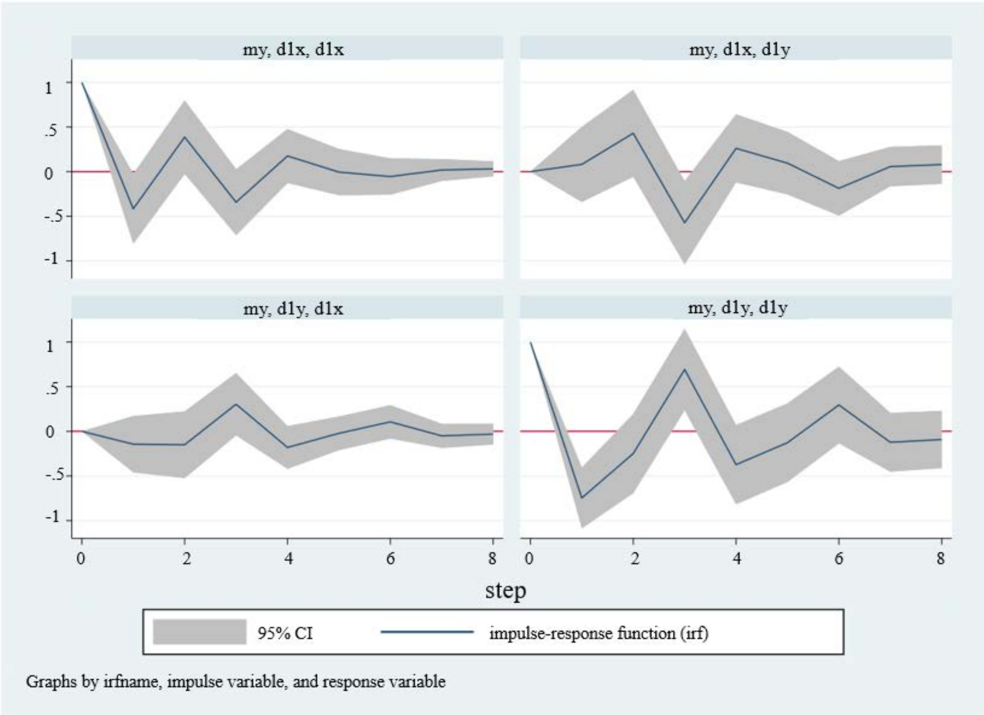

Figure 2. Financial and optional consumer industry pulse response analysis

3.2.3 Financial and major consumer industry

The premise of the Granger causality test is that the sample data series is stationary, so the data is first subjected to a unit root stationarity test.

As shown in the Table 8, it can be concluded that the major consumer industry series is stationary.

Table 8. Major consumer industry stability test

Dickey-Fuller Test for unit root			Number of obs =	38
			Interpolated Dickey-Fuller	
	Test Statistic	**1% Critical Value**	**5% Critical Value**	**10% Critical Value**
Z(t)	**-5.662**	**-4.260**	**-3.548**	**-3.209**

MacKinnon approximate p-value for Z(t) = **0.000**

Using multiple judgment criteria such as FPE, AIC, SBIC, HQIC, and LR tests as shown in Table 9, the optimal lag order of the model is determined to be 3.

Table 9. Lag term order selection of financial and major consumer industry

Selection-order Criteria

Sample: **7-39** Number of obs = 33

Lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	**-146.371**				**27.5631**	**8.99219**	**9.02271**	**9.08289**
1	**-120.397**	**51.948**	**4**	**0.000**	**7.284**	**7.66043**	**7.75198**	**7.93252**
2	**-116.847**	**7.1**	**4**	**0.131**	**7.5131**	**7.6877**	**7.84028**	**8.14119**
3	**-108.648**	**16.398***	**4**	**0.003**	**5.87404***	**7.43322***	**7.64683**	**8.0681**
4	**-104.816**	**7.6647**	**4**	**0.105**	**6.02516**	**7.44338**	**7.71803**	**8.25965**

Endogenous: d2y d2x

Exogenous: _cons

As shown in the Table 10, there is a causal relationship between the financial industry and the primary consumer.

Table 10. Financial and major consumer industry Granger causality test

Granger Causality Wald Tests				
Equation	**Excluded**	**chi2**	**df**	**Prob > chi2**
d2y	d2x	**6.0204**	**3**	**0.111**
d2y	ALL	**6.0204**	**3**	**0.111**
d2x	d2y	**10.296**	**3**	**0.016**
d2x	ALL	**10.296**	**3**	**0.016**

As shown in the Figure 3, the fluctuation in the stock prices of the financial industry has a positive impact on the primary consumer industry. As shown in the figure, when there is a fluctuation in the financial industry, it has a positive impact on the energy industry, reaching its peak in the first period. Afterward, the positive impact diminishes, gradually becoming negative, reaching its peak in the third period. After the fourth period, it gradually turns into a positive impact, with alternating positive and negative effects after the fifth period. When there are fluctuations in the primary consumer industry, the impact on the financial industry is not significant.

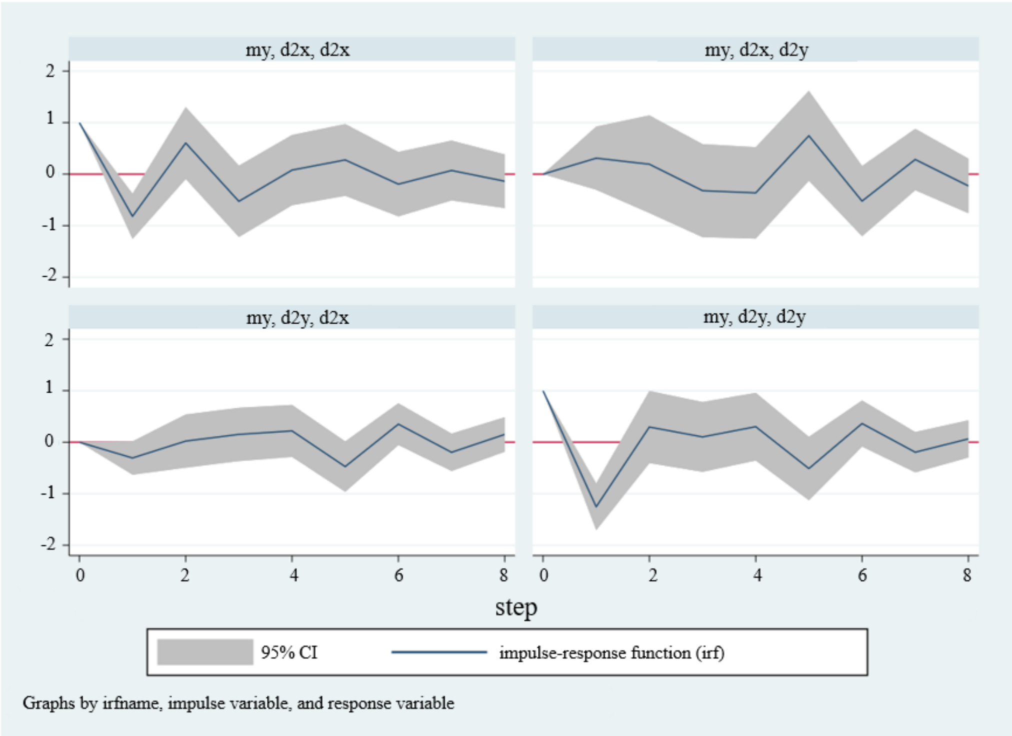

Figure 3. Financial and major consumer industry figure pulse response analysis

3.2.4 The financial and information technology industry

The premise of the Granger causality test is that the sample data series is stationary, so the data is first subjected to a unit root stationarity test.

As shown in the Table 11, it can be concluded that the information technology industry series is stationary.

Table 11. Information technology industry stability test

Dickey-Fuller Test for unit root			Number of obs =	38
			Interpolated Dickey-Fuller	
	Test Statistic	**1% Critical Value**	**5% Critical Value**	**10% Critical Value**
Z(t)	**-7.056**	**-4.260**	**-3.548**	**-3.209**
MacKinnon approximate p-value for Z(t) = **0.000**				

Using multiple judgment criteria such as FPE, AIC, SBIC, HQIC, and LR tests as shown in Table 12, the optimal lag order of the model is determined to be 3.

Table 12. Lag term order selection of information technology industry

Selection-order Criteria
Sample: **5-39** Number of obs = 35

Lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	**-124.845**				**4.81901**	**7.24829**	**7.27897***	**7.33717***
1	**-123.965**	**1.7609**	**4**	**0.780**	**5.76406**	**7.42655**	**7.51859**	**7.69318**
2	**-123.023**	**1.8826**	**4**	**0.757**	**6.88619**	**7.60134**	**7.75474**	**8.04572**
3	**-112.178**	**21.691**	**4**	**0.000**	**4.68952***	**7.21015***	**7.42492**	**7.83229**
4	**-111.538**	**1.2789**	**4**	**0.865**	**5.75487**	**7.40219**	**7.67831**	**8.20208**

As shown in the Table 13, based on the test results, it is evident that there is a causal relationship.

Table 13. Information technology industry Granger causality test

Granger Causality Wald Tests				
Equation	**Excluded**	**chi2**	**df**	**Prob > chi2**
y	x	**8.6866**	**3**	**0.034**
y	ALL	**8.6866**	**3**	**0.034**
x	y	**13.65**	**3**	**0.003**
x	ALL	**13.65**	**3**	**0.003**

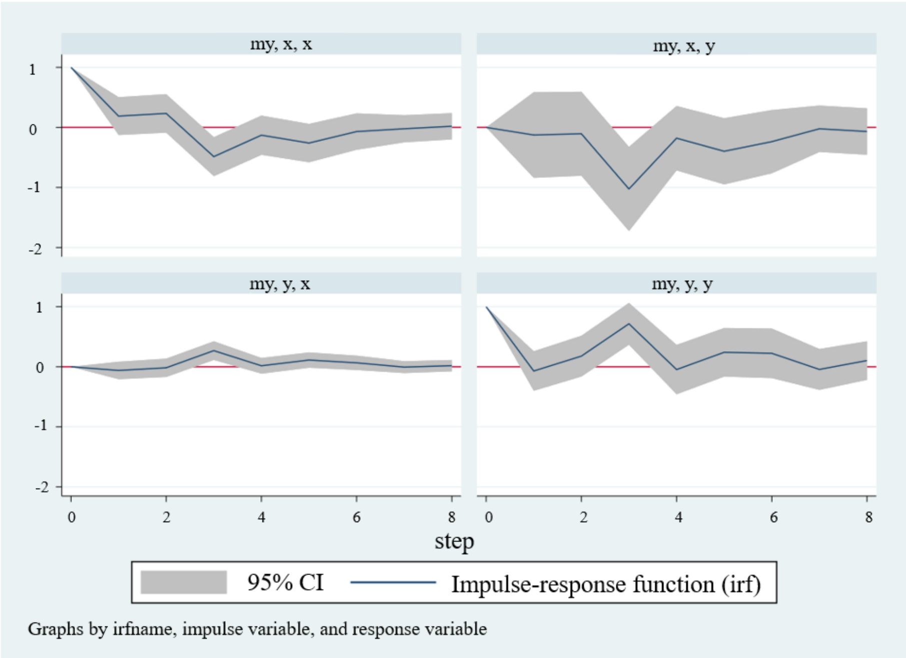

Figure 4. Information technology industry pulse response analysis

As shown in the Figure 4, the fluctuations in stock prices within the financial industry will have a negative impact on the information technology industry. As seen in the graph, when there are fluctuations in the financial sector, it negatively impacts the information industry, reaching its lowest point in the third period and gradually calming after the seventh period.

The stock price fluctuations in the information technology industry will have a positive impact on the financial industry. As shown in the graph, when there are fluctuations in the information technology sector, it positively impacts the financial industry, reaching its peak in the third period, gradually reducing after the fourth period, and stabilizing thereafter.

3.2.5 Financial industry and healthcare industry

The premise of the Granger causality test is that the sample data series is stationary, so the data is first subjected to a unit root stationarity test.

After conducting the stationarity analysis on the data, as shown in the Table 14, it is known that the healthcare industry series is stationary.

Table 14. Healthcare industry stability test

Dickey-Fuller Test for unit root		Number of obs =	38
		Interpolated Dickey-Fuller	
Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
Z(t) **-4.839**	**-4.260**	**-3.548**	**-3.209**
MacKinnon approximate p-value for Z(t) = **0.000**			

Using multiple judgment criteria such as FPE, AIC, SBIC, HQIC, and LR tests as shown in Table 15, the optimal lag order of the model is determined to be 2.

Table 15. Lag term order selection of healthcare industry

Selection-order Criteria
Sample: **7-39** Number of obs = 33

Lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	-162.071				71.3776	9.9437	9.97422	10.0344
1	-135.288	53.567	4	0.000	17.9599	8.56289	8.65444	8.83498
2	-127.208	16.16	4	0.003	14.0773*	8.31561	8.4682*	8.7691
3	-125.036	4.3433	4	0.362	15.8592	8.42642	8.64004	9.06131
4	-118.843	12.385	4	0.015	14.0991	8.29354	8.56819	9.10982

As shown in the Table 16, granger causality test shows the existence of a causal relationship.

Table 16. Healthcare industry Granger causality test

Granger Causality Wald Tests				
Equation	Excluded	chi2	df	Prob > chi2
d2y	d2x	**1.6446**	**2**	**0.439**
d2y	ALL	**1.6446**	**2**	**0.439**
d2x	d2y	**7.1133**	**2**	**0.029**
d2x	ALL	**7.1133**	**2**	**0.029**

As shown in the Figure 5, the fluctuations in stock prices within the healthcare industry will have a negative impact on the financial industry. As shown in the graph, when there are fluctuations in the healthcare industry, it negatively impacts the financial sector, reaching its lowest point in the second period. It gradually turns into a positive impact after the second period, and after reaching the maximum positive effect in the third period, the positive effect diminishes, turning negative again, and alternating between positive and negative effects after the sixth period.

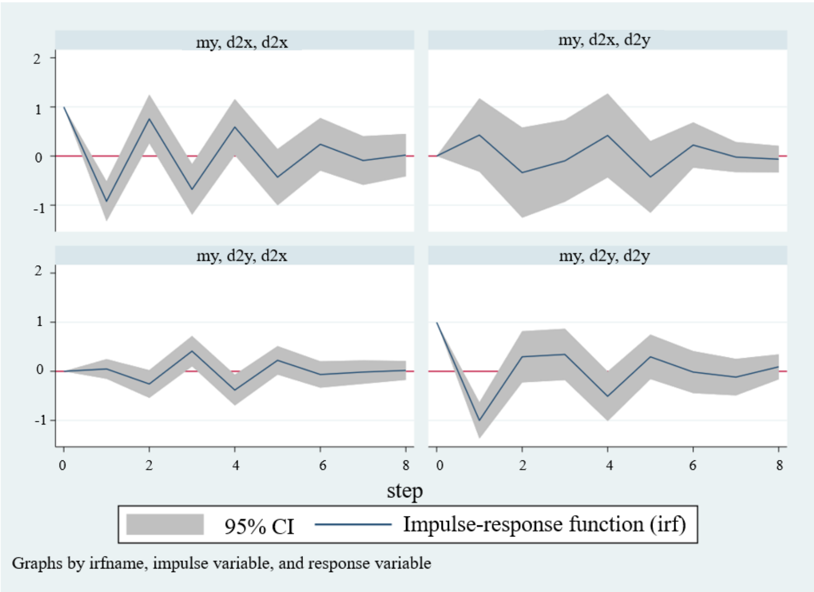

Figure 5. Healthcare industry pulse response analysis

4. Conclusion

The paper first analyzed the current difficulties faced by the Chinese stock market and the reasons for stock price fluctuations. Subsequently, a total of 429 data points related to the stock price changes of 11 industries in the CSI 300 index were collected from January 1, 2024, to March 1, 2024. The data was then used to analyze the impulse response functions of the associated industries with the financial market using the VAR model. The following conclusions were reached:

Currently, the technology and financial industries serve as pivotal points for stock price fluctuations in the economic market. Their fluctuations can lead to widespread negative impacts on other associated industries. Regulatory authorities lack independence, and the regulatory level is not high. Additionally, excessive intervention by management in the stock market often leads to continuous decline. Furthermore, issues like "difficult entry" and "difficult exit" in the Chinese stock market have resulted in numerous unpromising companies, hindering overall stock market development when negative impacts occur. In the context of China's aging population, the healthcare industry has become a pivotal player. The status of the healthcare industry has been elevated unprecedentedly, leading to increased attention. The government has gradually intensified drug regulation and invested significant funds in the biotechnology industry, making the entire healthcare industry one of the few sectors outside the financial industry that is not overly affected by stock price fluctuations.

This indicates that we may increase investment in the healthcare industry to seek opportunities in the stock market downturn. The information technology industry has been less affected by the post-pandemic situation compared to transportation and service industries. Therefore, at present, the information technology industry is relatively safer for investors. Additionally, like the biotechnology industry, it has lower reliance on the financial market compared to other industries. As a result, during significant fluctuations in the financial market, there may even be positive ripple effects from a long-term perspective.

Data Availability

The data used to support the research findings are available from the corresponding author upon request.

Conflicts of Interest

The authors declare no conflict of interest.

References

Bohannon, A. W., Lawhern, V. J., Waytowich, N. R., & Balan, R. V. (2020). The autoregressive linear mixture model: A time-series model for an instantaneous mixture of network processes. *IEEE Trans. Signal Process.*, *68*: 4481-4496. https://doi.org/10.1109/TSP.2020.3012946.

Chen, W., Hou, X. L., Jiang, M. R., & Jiang, C. (2022). Identifying systemically important financial institutions in complex network: A case study of Chinese stock market. *Emerg. Mark. Rev.*, *50*: 100836. https://doi.org/10.1016/j.ememar.2021.100836.

Gourène, G. A. Z., Mendy, P., & Ake, G. M. N. G. (2019). Multiple time-scales analysis of global stock market spillovers effects in African stock markets. *Int. Econ.*, *157*: 82-98. https://doi.org/10.1016/j.inteco.2018.09.001.

Hu, S. Y., Gu, Z. Y., Wang, Y. F., & Zhang, X. L. (2019). An analysis of the clustering effect of a jump risk complex network in the Chinese stock market. *Physica A Stat. Mech. Appl.*, *523*: 622-630. https://doi.org/10.1016/j.physa.2019.01.114.

Kou, G., Chao, X. R., Peng, Y., & Wang, F. (2022). Network resilience in the financial sectors: advances, key elements, applications, and challenges for financial stability regulation. *Technol. Econ. Dev. Econ.*, *28*(2): 531-558. https://doi.org/10.3846/tede.2022.16500.

Lai, Y. J. & Hu, Y. B. (2021). A study of systemic risk of global stock markets under COVID-19 based on complex financial networks. *Physica A Stat. Mech. Appl.*, *566*: 125613. https://doi.org/10.1016/j.physa.2020.125613.

Li, S. F., Zhang, H., & Yuan, D. (2019). Investor attention and crude oil prices: Evidence from nonlinear Granger causality tests. *Energy Econ.*, *84*: 104494. https://doi.org/10.1016/j.eneco.2019.104494.

Liu, J. M., Wu, C., & Li, Y. L. (2019). Improving financial distress prediction using financial network-based information and GA-based gradient boosting method. *Comput. Econ.*, 53: 851-872. https://doi.org/10.1007/s10614-017-9768-3.

Mylonidis, N. & Kollias, C. (2010). Dynamic European stock market convergence: Evidence from rolling cointegration analysis in the first euro-decade. *J. Bank. Financ.*, *34*(9): 2055-2063. https://doi.org/10.1016/j.jbankfin.2010.01.012.

Nishimura, Y., Tsutsui, Y, & Hirayama, K. (2016). The Chinese stock market does not react to the Japanese market:

Using intraday data to analyse return and volatility spillover effects. *Jpn. Econ. Rev.*, *67*(3): 280-294. https://doi.org/10.1111/jere.12086.
Oravecz, Z., & Vandekerckhove, J. (2023). Quantifying evidence for-and against-granger causality with bayes factors. *Multivar. Behav. Res.*, 1-11. https://doi.org/10.1080/00273171.2023.2214890.
Rong, Z., Ma, K., Gang, D., & Chen, S. Z. (2019). Study on the short-term and long-term Granger causality relationship between China's domestic and imported timber prices. *J. For. Res.*, *24*(3): 131-136. https://doi.org/10.1080/13416979.2019.1609743.
Rossi, B., & Wang, Y. R. (2019). Vector autoregressive-based Granger causality test in the presence of instabilities. *Stata J.*, *19*(4), 883-899. https://doi.org/10.1177/1536867X19893631.
Shahbaz, M., Jam, F. A., Bibi, S., & Loganathan, N. (2016). Multivariate granger causality between CO_2 emissions, energy intensity and economic growth in Portugal: Evidence from cointegration and causality analysis. *Technol. Econ. Dev. Econ.*, *22*(1), 47-74. https://doi.org/10.3846/20294913.2014.989932.
Si, J. J., Zhou, J. S., Gao, X. Y., Ze, W., Tao, W., & Zhao, Y. R. (2022). Reconstructing a complex financial network using compressed sensing based on low-frequency time series data. *Financ. Res. Lett.*, *49*: 103097. https://doi.org/10.1016/j.frl.2022.103097.
Slim, S., Koubaa, Y., & BenSaida, A. (2017). Value-at-Risk under Lévy GARCH models: Evidence from global stock markets. *J. Int. Financ. Mark. Inst. Money*, *46*, 30-53. https://doi.org/10.1016/j.intfin.2016.08.008.
Sun, H. & Yu, B. (2020). Forecasting financial returns volatility: A GARCH-SVR model. *Comput. Econ.*, *55*(2): 451-471. https://doi.org/10.1007/s10614-019-09896-w.
Usman, K. (2023). The nexus between remittance, exchange rate and economic growth of E7 economies: Frequency domain analysis. *Heliyon*, *9*: e21554. https://doi.org/10.1016/j.heliyon.2023.e21554.
Xiao, M., Tao, Z. P., Gu, Z. Y., Li, Z. X., & Chen, X. H. (2023). New practice for investors in Chinese stock market: From perspective of fractionally integrated realized GARCH model. *Heliyon*, *9*: e14017. https://doi.org/10.1016/j.heliyon.2023.e14017.
Zhang, W. P., Zhuang, X. T., & Li, Y. S. (2019). Dynamic evolution process of financial impact path under the multidimensional spatial effect based on G20 financial network. *Physica A Stat. Mech. Appl.*, *532*: 121876. https://doi.org/10.1016/j.physa.2019.121876.