PHEIC, Investor Sentiment, Vaccination, and Stock Market: The Case Study on COVID-19

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Abstract

The study aims to research the association among the PHEIC, investor sentiment, vaccination, and stock market using case study on COVID-19. The data includes seven variables' daily data from Mar 2021 to Oct 2022 in China and analyzed the association by co-integration test, the ARDL model, and the VAR model. Based on the co-integration test and ARDL model, the results show a significant long-term and short-term relationship among the COVID-19 cases, investor sentiment, COVID-19 vaccination, and the stock market. The impulse response function analysis found that when the COVID-19 cases, investor sentiment, and COVID-19 vaccination respectively received the impulse, the rest variables showed rapid and significant response in the initial periods but converge by the time except COVID-19 cases and vaccination seems long effect response. This study uses econometrics to analysis the association, which contributes to enrich the knowledge of behavior finance during the pandemic. And, the study takes most all

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the potential impact variables, determining the importance of investor sentiment and COVID-19 vaccination during the pandemic. This study enables investors and policymakers to better understand as COVID-19 as one kind of PHEIC for effective decision-making, risk management and sustainable protection on PHEIC.

Keywords: ARDL, VAR, ECM, COVID-19, Investor Sentiment, Vaccination, Stock Market

PHEIC, ความรู้สึกของนักลงทุน, ความครอบคลุมในการฉีดวัคซีน, ตลาดหุ้น : กรณีศึกษาเกี่ยวกับ COVID-19

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บทคัดย่อ

การศึกษานี้มีจุดมุ่งหมายเพื่อวิจัยความสัมพันธ์ระหว่าง PHEIC ความรู้สึกของนักลงทุน ความครอบคลุมของการฉีดวัคซีนในประเทศ และตลาดหุ้นในประเทศจีนโดยข้อมูลประกอบด้วยข้อมูลรายวันจากเดือนมีนาคม 2021 ถึงเดือนตุลาคม 2022 ในประเทศจีน และวิเคราะห์ความสัมพันธ์โดยการทดสอบ cointegration test แบบจำลอง ARDL และ VAR โดยพบว่าจากการทดสอบ cointegration และแบบจำลอง ARDL ผลลัพธ์แสดงให้เห็นว่าความสัมพันธ์ระยะยาวและระยะสั้นระหว่างตัวแปรจำนวนคนที่เป็น COVID19 ความรู้สึกของนักลงทุน ความครอบคลุมในการฉีดวัคซีน COVID19 และตลาดหุ้นในประเทศจีน มีความสัมพันธ์อย่างมีนัยยะสำคัญทางสถิติ การวิเคราะห์ฟังก์ชันการตอบสนองต่อการกระตุ้น (Impulse Response Function) พบว่า เมื่อจำนวนคนติด COVID19 ความรู้สึกของนักลงทุน และความครอบคลุมการฉีดวัคซีน COVID19 ได้รับการกระตุ้นตัวแปรในตลาดหุ้นแสดงการตอบสนองที่รวดเร็วและมีนัยสำคัญในช่วงแรก แต่จะเข้าสู่จุดสมดุลเมื่อเวลาผ่านไป ยกเว้นจำนวนผู้ติดเชื้อ COVID19 และความครอบคลุมในการฉีดวัคซีนที่ดูเหมือนจะมีผลตอบสนองในระยะยาว การศึกษานี้ใช้เศรษฐมิติ

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ในการวิเคราะห์ความสัมพันธ์ซึ่งมีส่วนช่วยเสริมความรู้เกี่ยวกับการเงินพฤติกรรมในช่วงการระบาด นอกจากนี้ การศึกษายังครอบคลุมตัวแปรที่มีผลกระทบที่เป็นไปได้ทั้งหมด เพื่อกำหนดความสำคัญของความรู้สึกของนักลงทุนและการฉีดวัคซีน COVID19 ในช่วงการระบาด การศึกษานี้ช่วยให้นักลงทุนและผู้กำหนดนโยบายเข้าใจปัจจัยที่มีผลกระทบต่อตลาดหุ้นในสถานการณ์ไม่ปกติได้ดีขึ้น

คำสำคัญ: ARDL VAR COVID19 ความรู้สึกของนักลงทุน ความครอบคลุมในการฉีดวัคซีน ตลาดหุ้น

Introduction

Public Health Emergency of International Concern (PHEIC) is proposed to prevent and reduce the transnational transmission of disease to raise the potential interference in international trade and traffic that probably cause economic losses. The COVID-19 outbreak has affected about 7 billion people in more than 210 countries within three months, likely surpassing all known PHEIC on the infection (WHO, 2020). Pandemic infectious diseases contain significant potential threats to the economy and society (Bhuyan, Lin, & Ricci, 2010; Chen, Jang, & Kim, 2007; Mei-Ping, Chien-Chiang, Yu-Hui, & Wen-Yi, 2018; Nippani & Washer, 2004). The COVID-19 crisis has led to unprecedented social and economic dislocation, accompanied by sharp declines and recoveries in stock markets (Pavlova & Boyrie, 2022). COVID-19, as the most serious PHEIC since the end of the World War II, China was the first country to report the outbreak and take related preventive measures. It is reasonable to believe that China's data are possibly representative.

The dynamics of stock markets reflect the performance of economies during the COVID-19 pandemic, which is contagious and can affect many of the world's economies and their respective stock markets simultaneously. During the COVID-19 outbreak, the Dow Jones Industrial index, the S&P 500 index, and the NASDAQ fluctuate wildly, especially around the initial period as the PHEIC. Besides, China's two major stock markets, 3,188 stocks on the Shanghai and Shenzhen stock exchanges (SSE and SZSE) fell by the daily limit on the first day of trading after COVID-19 has been announced as PHEIC. With the SSE and SZSE indexes closing, the SSE index experienced its most significant drop since 2015. COVID-19 is an unprecedented event that has harmed financial markets (Al-Awadhi, Alsaifi, Al-Awadhi, & Alhammadi, 2020; Kapar, Buigut, & Rana, 2022; Schell, Wang, & Huynh, 2020; Topcu & Gulal, 2020).

In China's two major stock markets, the composition of Chinese investors is relatively special, in which individual investors account for more than 70%, and the market value held by individual investors accounts for about 25% of the total market value, which is quite high in the world. Meanwhile, sentiment constitutes powerful, universal, and predictable decision-making drivers, and essential patterns emerge in the mechanisms by which emotions influence judgment and choice in different domains (Lerner, Li, Valdesolo, & Kassam, 2015).

The COVID-19 pandemic has led to a sharp decline in the sentiment expressed globally. Lockdown policies have moderate or no effect on the sentiment expressed, with significant heterogeneity among countries (Wang; et al., 2022). The escalation of COVID-19 in Asian countries has led to negative sentiment (Lwin et al., 2022).

As the comprehensive vaccination of COVID-19 has become one of the mainstream ways of pandemic prevention in China, people's lives have gradually back pre-pandemic, and the real economy has gradually returned as well, which probably reflect in the stock market, even affect investor sentiment. Global stock markets have conveyed vital information about the market's overall expectations regarding the economic value of COVID-19 vaccine development ahead of the start of public vaccination. When different phases of human clinical trials for COVID-19 vaccines began, global stock markets reacted significantly positively, especially at the start of phase 3 trials (Chan, Chen, Wen, & Xu, 2022).

As a kind of PHEIC, the COVID-19 pandemic has characteristics on long-term and disruptive, sustainable protection on human health and wealth is indeed. The impact of the COVID-19 pandemic on investor sentiment has affected investment decision-making, which has been reflected in the stock market. Meanwhile, the impact of the pandemic on the real economy has also been reflected in the stock market performance. Besides, with the emergence of the COVID-19 vaccine, the corresponding studies on the vaccine, stock market, and investor sentiment have also emerged. However, the COVID-19 cases, investor sentiment, COVID-19 vaccination, and the stock market have been less discussed. Therefore, this paper decides to fill this research gap.

This paper aims to study whether there is a relationship among the COVID-19 pandemic, investor sentiment, COVID-19 vaccination, and the stock market. This paper uses modelling analysis to establish a financial analysis VAR model, co-integration test and ARDL model for data analysis. It may offer provides some theoretical reference for policy makers or investors in the future. Moreover, it could enrich behavioral finance theory as involve investor sentiment in the study.

This paper includes the following sections, section 1 introduction, section 2 literature review, section 3 data and methodology, section 4 results and discussion, the section 5 is the conclusion.

Literature review

This section mainly reviews three aspects, the first aspect is on the introduction of PHEIC, the second aspect is investor sentiment, COVID-19, and stock market, then we review the investor sentiment, stock market, and COVID-19 vaccination.

PHEIC

Under the International Health Regulations (2005), the World Health Organization will declare a public health Emergency of international Concern (PHEIC) if the situation meets certain criteria (WHO, 2008). PHEIC is the highest level of alert the WHO can issue and has only been used six times since 2009, including: H1N1(2009), EBOV (2014), Poliomyelitis (2014), Zika (2016), EBOV (2018), and COVID19. And the COVID-19 is the worst global crisis since World War II, which is caused by a disease that threatens everyone in the world, and the resulting economic impact will bring about an unprecedented recession.

PHEIC often exacerbate already unfavorable working conditions that has been a driver of health worker strikes in the North and the South, particularly in Asia and Africa (Craveiro et al., 2023). PHEIC has a positive and significant impact on the portfolio of insurance companies through investor sentiment, and this impact has a lasting effect (Shang et al., 2022). Comparing the previous PHEIC, COVID-19 is an extremely rare global pandemic in human history and the most serious global public health crisis since World War II.

Investor Sentiment, COVID-19, and Stock Market

Emotions and decision-making complement each other (Morris, 2000). Therefore, investor sentiment is associated with stock-market-related decisions (Bower, 1991; Forgas & Bower, 1987; Schwarz & Clore, 1983; Schwarz & Norbert, 1990). Quality values influence negative emotions and lead to emotion-centered decision-making (Luce, Payne, & Bettman, 2000). Emotions affect the accuracy of information processing and decision-making (Au, Chan, Wang, & Vertinsky, 2003).

Due to the confinement related policies on COVID-19, interaction and social contact are greatly reduced, which can affect emotional recognition (Meléndez et al., 2020). Various economic uncertainty indicators before and during the COVID-19 pandemic showed great uncertainty in the response to the pandemic (Altig; et al., 2020). Investor sentiment driven by coronavirus-related news (CRNS) and economic-related announcements related to the coronavirus outbreak (ERAs) had an impact on investor sentiment (Singh, Imam, Wibowo, & Grandhi, 2022; Y. Sun, Bao, & Lu, 2021). Under the influence of investor sentiment, COVID-19 has a negative impact on stock returns (L. Sun & Shi, 2022). The impact of the COVID-19 pandemic on major emerging and developed stock markets provides that lockdowns and the spread have led to immediate financial contagion (Samitas, Kampouris, & Polyzosa, 2022).

Investor Sentiment, Stock Market, and COVID-19 vaccination

Attitudes towards vaccination vary widely depending on the characteristics of specific countries and regions. Different factors work together strongly influenced their investment strategies and vaccination often reduces fear (Reis, 2022). The COVID-19 pandemic has a significant negative impact on the mean of Canadian stock returns, a positive impact on the volatility, and the vaccination program has reversed these detrimental effects (Apergis, Mustafa, & Malik, 2022). The vaccination campaign has not had a significant impact on the Indian stock market (R, Sinha, & Mandal, 2021). COVID-19 vaccination increases fear and economic anxiety (Awijen, Zaied, & Nguyen, 2022). There is a strong and significant connectivity relationship between COVID-19 vaccination rates and S&P 500 returns (Khalfaoui, Nammouri, Labidi, & Jabeur, 2021). The highly negative bipolar sentiment reflected the damaging impact on the stock market until a vaccine for COVID-19 is developed, the only respite for financial markets to recover is a temporary reduction in COVID-19 infections (Eachempati, Srivastava, & Panigrahi, 2021). The emergence of new variants of COVID-19 has led to high levels of global uncertainty, and investor concerns about COVID-19 appear to be having a negative impact on financial markets (Cevik, Altinkeski, Cevik, & Dibooglu, 2022).

Based on the above, it is found that COVID-19 is a PHEIC that is worth to study, and the investor sentiment has impact on the financial related decision-making, then effect on the stock market, COVID-19 has influence on the investor sentiment, and COVID-19 vaccination also affect the investor sentiment. Previous studies have given good examples on the variables even analysis the association among them. However, there are lack of research that discus the association on all variables together through financial models. Therefore, the study attempts to fill the gap.

Data and Methodology

Data

The study used the CSI 300 index to study China's stock market (Chu, Goodell, Li, & Zhang, 2021; Xu & Pu, 2022; Zhou, Rao, & Lu, 2020). The stock market dynamics are analyzed using daily data from Mar 2021 to Oct 2022 includes the daily market volatility, daily market index return, daily market trading volume, and daily market turnover rate obtained from the Wind Info. (Wind Information Co., Ltd). The Investor Sentiment index is referred to the China Investor Sentiment Index (CISI). The COVID-19 cases related data and COVID-19 vaccination was published by the National Health Commission of the People's Republic of China (nhc.gov.cn).

COVID19 Confirmed Cases

The statistical data on COVID19 was collected from the National Health Commission of China (nhc.gov.cn), which is cumulative data. The daily total confirmed cases of COVID19 includes the daily active cases that included in the confirmed case who still tests positive., daily recovery cases that is the COVID19 confirmed cases have tested negative for nucleic acid and have not relapsed after 14 days of medical quarantine, and daily deaths that is the daily case died due to COVID19, which are calculated in t days as:

t day's COVID19 confirmed cases

= (t day's active cases + t day's recovery cases + t day's deaths)

Investor Sentiment Index

The investor sentiment index in this paper refers to the China Investor Sentiment Index (CISI) to measure Chinese investor Sentiment.

COVID19 Vaccination

The statistical data on COVID19 was collected from the National Health Commission of China (nhc.gov.cn). and the unit in the study is 1million people.

Market Volatility

In this study, the market volatility statistics are from the daily CSI 300 index. The specified interval is divided into several sample intervals according to the set period, and then the average standard deviation of the return rate of the specified period is calculated. For example, if the period is set to month, the calculated result is the standard deviation of the monthly return rate. Then the data goes through the calculation:

$$\text{Volatility} = \left\{\sum\left[\left(R_i - \left(\sum \frac{R_i}{N}\right)^\wedge 2\right)\right] /(N-1)\right]\right\}^\wedge 0.5$$

According to the calculation cycle (daily refers to the trading cycle; week, month, and average year refer to the calendar period) in the selected period, N intervals are incomplete. Calendar periods included at the beginning and end are omitted), and the closing price of the last trading day of each interval is obtained as Ri.

Market Index Return

The statistical data of Market Index Return from the daily CSI 300 index. The data goes through the calculation:

$$\text{Market Index Return} = \frac{\text{t day's close index - (t-1) day's close index}}{\text{t-1 day's close index}}$$

Market Trading Volume

For the stock trading volume in the study, we collected the data from the daily CSI 300 index. The unit of market trading volume is 100 million in the study, the data goes through the calculation:

$$\text{Trading Volume} = \text{Price} \times \text{Volume} - \text{Commission}$$

Market Turnover Rate

The study collected the market turnover rate database of CSI 300. The formula for calculating the turnover rate is:

$$\frac{\text{Trading Volume}}{\text{Circulating Capital}} \times 100\%$$

Methodology

A vector autoregressive (VAR) model is a statistical model used to analyze the relationship between multiple time series variables. It estimates how each variable is influenced by its own past values and the past values of the other variables in the system. The VAR model assumes that the variables are interdependent and affect each other over time. It is commonly used in economics, finance, and other fields for forecasting and understanding the dynamics between different economic variables.

The VAR (vector autoregressive) model formulate as:

$$\boldsymbol{Y_t = A_1 Y_{t-1} + A_2 Y_{t-2} + \ldots + A_p Y_{t-p} + U_t} \tag{1}$$

where:

$\boldsymbol{Y_t}$ is a vector of endogenous variables at time $\boldsymbol{t}$.

$\boldsymbol{A_1, A_2, \ldots A_p}$ are matrices of parameters.

$\boldsymbol{Y_{t-1}, Y_{t-2}, \ldots Y_{t-p}}$ are lags of the endogenous variables.

$\boldsymbol{U_t}$ is a vector of error terms at time $\boldsymbol{t}$.

In the study $\boldsymbol{Y_t}$ is a vector of the seven variables that includes the COVID-19 cases, COVID-19 vaccination, investor sentiment, daily market volatility, daily market index return, daily market trading volume, and daily market turnover rate at time $\boldsymbol{t}$.

When establishing a VAR model based on time series data, the augmented Dickey-Fuller (ADF) test is used to conduct a unit root test:

$$\boldsymbol{y_{(t)} = c + \rho y_{(t-1)} + \beta_1 \Delta y_{(t-1)} + \beta_2 \Delta y_{(t-2)} + \ldots \beta_k \Delta y_{(t-k)} + \varepsilon_t} \tag{2}$$

where $\boldsymbol{y_{(t)}}$ is the variable being tested for a unit root, $\boldsymbol{c}$ is a constant, $\boldsymbol{\rho}$ is the coefficient on the lagged dependent variable, $\boldsymbol{\Delta y_{(t-1)}}$ is the first difference of the variable, $\boldsymbol{\beta_1, \beta_2, \ldots, \beta_k}$ are coefficients on the lagged differences, $\boldsymbol{\varepsilon_t}$ is the error term, and $\boldsymbol{k}$ is the number of lags in the model.

The null hypothesis of the ADF test is that $\rho = 1$, indicating the presence of a unit root in the time series. The alternative hypothesis is that $\rho < 1$, indicating that the time series is stationary and does not have a unit root. The test statistic compares the estimated value of ρ to its standard error, and the critical values are obtained from tables, depending on the sample size and level of significance (Dickey & Fuller, 1979, 1981).

This study uses Akaike's Information Criterion (AIC), Bayesian Information Criterion (BIC), and Hannan-Quinn Information Criterion (HQIC) statistics to select the optimal lag order.

$$AIC = T * ln(det(SSE / T)) + 2 * k * p \tag{3}$$

$$BIC = T * ln(det(SSE / T)) + k * p * ln(T) \tag{4}$$

$$HQIC = T * ln(det(SSE / T)) + 2 * k * p * ln(lnT) \tag{5}$$

Where T is the sample size, SSE is the sum of squared residuals from the VAR model, k the number of variables, and the p is the number of lags.

Based on the empirical study variables, a seven-dimensional VAR model is constructed. In the study, we conducted the Impulse Response Function (IRF) to analysis the association among the variables. Based on the impulse response function, the i^{th} endogenous variable of an impact not only directly affects the case of a variable but i also pass through the dynamic structure of the VAR model to other endogenous variables. In $VAR\ (p)$ model, the cumulative response function of y_i caused by the impulse of y_j express as:

$$\varphi_{i=} \sum_{q=0}^{\infty} \theta_{ij}^{(q)} \tag{6}$$

The elements of the i^{th} row and j^{th} column of θ_q expresses as:

$$\theta_{ij}^{(q)} = \frac{\partial y_{i,t+q}}{\partial \varepsilon_{jt}}, q = 0, 1, 2 \dots, t = 1, 2, \dots, T \tag{7}$$

As a function of q, it describes the response of $y_{i,t+q}$ to the shock of one unit of ε_{jt} in the case that the disturbance term of the j^{th} variable increases by one unit in the period t. the other disturbance terms remain unchanged, and the disturbance terms in other periods are constant.

In the case of period $\boldsymbol{t}$, with other variables and early variables unchanged, $\boldsymbol{y_{t+q}}$ response to a unit impact of $\boldsymbol{u_{jt}}$ is:

$$\frac{\partial y_{t+q}}{\partial u_{jt}} = \frac{\partial y_{t+q}}{\partial \acute{\varepsilon}_t}\frac{\partial \varepsilon_t}{\partial u_{jt}} = \theta_q p_j \tag{8}$$

In this study, variables often interact with each other, making them difficult to sort. Therefore, the generalized impulse response analysis method is adopted here to avoid the deviation caused by improper sorting. The corresponding generalized impulse response function is:

$$\theta_{ij}^{(q)} = \sigma_{jj}{}^{-1/2}\theta_q \Sigma_{j,} q = 0, 1, 2 \ldots, \tag{9}$$

When the covariance matrix $\boldsymbol{\Sigma}$ is a diagonal matrix, the results of orthogonal pulses and optical pulses are consistent. When the covariance matrix $\boldsymbol{\Sigma}$ is off diagonal, the Cholesky orthogonal pulses are equal to the generalized pulses only at $\boldsymbol{j = 1}$.

Variance decomposition analysis the contribution degree of each structural shock to the change of endogenous variables, usually measured by the relative variance contribution rate. the variance decomposition method to grasp the influence relationship between variables quantitatively but relatively crudely proposed by (Sims, 1980). In the multivariable VAR model, the $\boldsymbol{i}^{\text{th}}$ variable $\boldsymbol{y_{it}}$ of $\boldsymbol{y_t}$ writes as:

$$y_{it} = \sum_{j=1}^{k}(\theta_{ij}^{(0)}\varepsilon_{jt} + \theta_{ij}^{(1)}\varepsilon_{jt-1} + \theta_{ij}^{(2)}\varepsilon_{jt-2} + \cdots),$$

$$i = 1, 2, \ldots, k, t = 1, 2, \ldots, T \tag{11}$$

If $\boldsymbol{Var(\varepsilon_{jt}) = \sigma_{jj}}$, then

$$E\left[(\theta_{ij}^{(0)}\varepsilon_{jt} + \theta_{ij}^{(1)}\varepsilon_{jt-1} + \theta_{ij}^{(2)}\varepsilon_{jt-2} + \cdots)^2\right] = \sum_{q=0}^{\infty}(\theta_{ij}^{(q)})^2\sigma_{jj}, i, j = 1, 2, \ldots, k \tag{12}$$

Then,

$$Var(y_{it}) = \sum_{j=1}^{k}\left\{\sum_{q=0}^{\infty}\left(\theta_{ij}^{(q)}\right)^2\sigma_{jj}\right\}, i = 1, 2, \ldots k \tag{13}$$

The variance of $\boldsymbol{y_i}$ can be decomposed into $\boldsymbol{k}$ kinds of unrelated influences. Therefore, to determine the contribution degree of each disturbance term relative to the variance of $\boldsymbol{y_i}$, the relative variance contribution rate is defined as:

$$\boldsymbol{RVC_j \to (\infty) = \frac{\sum_{q=0}^{\infty}\left(\theta_{ij}^{(q)}\right)^2 \sigma_{jj}}{Var(y_{it})} = \frac{\sum_{q=0}^{\infty}\left(\theta_{ij}^{(q)}\right)^2 \sigma_{jj}}{\sum_{j=1}^{k}\left\{\sum_{q=0}^{\infty}\left(\theta_{ij}^{(q)}\right)^2 \sigma_{jj}\right\}}}\ ,$$

$$\boldsymbol{i, j = 1, 2, \dots, k} \qquad (14)$$

It observes the influence of the $\boldsymbol{j}^{\text{th}}$ variable on the $\boldsymbol{i}^{\text{th}}$ variable according to the contribution of the $\boldsymbol{j}^{\text{th}}$ variable to the variance of $\boldsymbol{y_i}$ based on the variance of the impulse. In practical application, it is impossible to evaluate the model by the sum of ∞. If the model satisfies that the stationability $\boldsymbol{\theta_{ij}^{(q)}}$ decreases geometrically with the increase of $\boldsymbol{q}$, only finite terms are usually taken for the calculation.

(Hendry, 1995) proposed the autoregressive distributed lag model for dynamic models. In this paper, ARDL model is used to test the long-term relationship between variables.

A typical ARDL model structure is shown below:

$$\boldsymbol{\emptyset(L, p)y_t = \sum_{i=1}^{k} \beta_i(L, q_i)x_{it} + \delta w_t + \varepsilon_t}$$

Here:

$$\boldsymbol{\emptyset(L, p) = 1 - \emptyset_1 L - \cdots - \emptyset_p L^p}$$

$$\boldsymbol{\beta_i(L, q_i) = 1 - \beta_{il} L - \cdots - \emptyset_{iq_i} L^{q_i}} \qquad (15)$$

where p represents the lag order of y_t, and q_i represents the lag order of x_{it}, the ith independent variable. L stands for hysteresis operator, defined as $L_{yt} = y_{t-1}$. w_t is the determination vector of row 1 column of s. First, estimate all possible values using the OLS method, a total of $(m+1)^{k+1}$ different ARDL models. The maximum lag item m is selected as required. Then, one of all the $(m+1)^{k+1}$ ARDL models are selected. In this paper, we will also estimate the corresponding error correction model to try to account for short-term effects.

Results & Discussion

The descriptive statistics include all data from a given set in Table 1, which includes seven variables' daily data from period Mar 2021 to Oct 2022.The time series starts from the COVID-19 vaccination data publication day.

Table 1: Descriptive Statistics

Description	COVID-19 Vaccination (million)	COVID-19 Confirmed Cases	Investor Sentiment	Market Index Return	Trading Volume (100 million)	Turnover Rate	Volatility
Mean	2444.626	145481.900	40.777	-0.001	143.834	0.516	17.959
Median	2896.705	103374.500	40.700	-0.001	138.542	0.498	16.670
Maximum	3439.802	260506.000	47.500	0.043	326.721	1.184	33.500
Minimum	82.846	90125.000	33.900	-0.049	78.560	0.274	9.310
Std. Dev.	1075.468	64224.150	2.083	0.012	37.428	0.138	5.520
Skewness	-0.901	0.645	0.171	-0.264	1.167	1.141	1.163
Kurtosis	2.526	1.575	3.376	4.526	5.350	5.270	3.648
Jarque-Bera	56.477	60.060	4.196	42.386	178.182	168.340	94.770
Probability	0.000	0.000	0.123	0.000	0.000	0.000	0.000
Sum	953404.100	56737954.000	15902.870	-0.339	56095.090	201.356	7003.910
Sum Sq. Dev.	450000000	1.6E+12	1688.334	0.052679	544941.3	7.358455	11853.51
Observations	390	390	390	390	390	390	390

Note: Data in column 1 to 2 adapted from nhc.gov.cn.; column 3 adapted from author calculated; column 4 to 6 adapted from Wind Information Co., Ltd.

As shown in Table 2, the unit root test results show the COVID-19 vaccination, investor sentiment, daily market index return, daily market trading volume, and daily market turnover rate is integrated of order zero (I (0)), daily market volatility is integrated of 1st -order (I (1)), and the COVID-19 cases is integrated of the 2nd -order (I (2)). Since the variables are stable at different orders, the Johansen cointegration test employed in the study.

Table 2: Results of unit root test

Variables	ADF-statistic	1% level	5% level	10% level	P-value	Order of integration
COVID-19 Vaccination	-3.472	-3.447	-2.869	-2.571	0.009**	I(0)
COVID-19 Confirmed Cases	-10.989	-3.982	-3.422	-3.134	0.000***	I(2)
Investor Sentiment	-5.077	-3.982	-3.422	-3.134	0.000***	I(0)
Market Index Return	-20.000	-3.982	-3.421	-3.133	0.000***	I(0)
Trading Volume	-5.166	-3.982	-3.421	-3.134	0.000***	I(0)
Turnover Rate	-5.088	-3.982	-3.421	-3.134	0.000***	I(0)
Volatility	-16.910	-3.982	-3.421	-3.134	0.000***	I(1)

Note: Group: All index, *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$

Based on the results shown in Table 2, that COVID-19 confirmed cases is stable on I (2), COVID-19 vaccination, investor sentiment, market index return, trading volume, and turnover rate are stable on I (0), and volatility is stable on I (1), a complete ARDL model was constructed to investigate whether there is a long-term cointegration relationship among the variables. We select the ARDL model containing system default criteria through experiments, and the model constructed according to the Akaike information criterion selected model: ARDL (2, 0, 2, 0, 0, 0, 0), as shown in Table 3. Based on the selected and constructed ARDL model, bounds testing is carried out. As shown in Table 4, the F statistic value is greater than the upper bound value at each significance level, so there is a long-term cointegration relationship between COVID-19 vaccination and the other variables in the study and based on Table 5 it also shows there is short-term association among variables.

Table 3: ARDL model selection (dependent variable: COVID-19 vaccination)

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
COVID-19 Vaccination (-1)	0.654	0.048	13.554	0.000
COVID-19 Vaccination (-2)	0.343	0.048	7.113	0.000
COVID-19 Confirmed Cases	0.000	0.000	-1.966	0.050
Investor Sentiment	0.651	0.479	1.360	0.175
Investor Sentiment (-1)	-0.567	0.500	-1.133	0.258
Investor Sentiment (-2)	-0.819	0.463	-1.769	0.078
Market Index Return	-81.071	74.783	-1.084	0.279
Trading Volume	-1.803	0.978	-1.844	0.066
Turnover Rate	502.758	268.875	1.870	0.062
Volatility	-0.135	0.157	-0.860	0.391
C	58.395	23.795	2.454	0.015
R-squared	1.000	Mean dependent var		2456.792
Adjusted R-squared	1.000	S.D. dependent var		1064.740
S.E. of regression	16.504	Akaike info criterion		8.473
Sum squared resid	102686.100	Schwarz criterion		8.585
Log likelihood	-1632.763	Hannan-Quinn criter.		8.518
F-statistic	161037.100	Durbin-Watson stat		2.047
Prob(F-statistic)	0.000***			

Note: *p-value<.05, **p-value<.01, ***p-value<. 001.p-values and any subsequent tests do not account for model selection.

Table 4: The results of bound test (dependent variable: COVID-19 vaccination)

F-Bounds Test	**Null Hypothesis:**	No levels relationship			
Test Statistic	**Value**	**k**	**Significant** Asymptotic: n=1000 10%	**I (0)** 1.99	**I (1)** 2.94
F-statistic	27.249	6	5% 2.50% 1% Finite Sample: n=80 10%	2.27 2.55 2.88 2.088	3.28 3.61 3.99 3.103
Actual Sample Size	388		5% 1%	2.431 3.173	3.518 4.485

Table 5: ARDL error correction regression (dependent variable: COVID-19 vaccination)

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
D (COVID-19 Vaccination (-1))	-0.343	0.048	-7.181	0.000
D (Investor Sentiment)	0.651	0.400	1.627	0.105
D (Investor Sentiment (-1))	0.819	0.403	2.033	0.043
CointEq (-1)*	-0.003	0.000	-14.901	0.000
R-squared	0.238	Mean dependent var		8.644
Adjusted R-squared	0.232	S.D. dependent var		18.658
S.E. of regression	16.353	Akaike info criterion		8.437
Sum squared resid	1.03E+05	Schwarz criterion		8.478
Log likelihood	-1632.763	Hannan-Quinn criteria.		8.453
F-statistic	27.249	Durbin-Watson stat		2.047
Prob(F-statistic)	0.000***			

Note: *p-value<.05, **p-value<.01, ***p-value<. 001.p-values and any subsequent tests do not account for model selection.

In the study, it respectively to use different depend variables to test. we continue to build the ARDL model with the dependent variable COVID-19 confirmed cases and select the optimal model as ARDL (4, 2, 0, 0, 0, 4, 0), as shown in Table 6. As shown in Table 7, the F statistic value is greater than the upper bound value at each significance level, so there seems a long-term cointegration relationship between COVID-19 confirmed cases and the other variables. Table 8 shows there is a significant short-term relationship among investor sentiment, vaccination, COVID-19 cases, and the stock market.

Table 6: ARDL model selection (dependent variable: COVID-19 confirmed cases)

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
COVID-19 Confirmed Cases (-1)	1.216	0.049	24.949	0.000
COVID-19 Confirmed Cases (-2)	0.038	0.079	0.482	0.630
COVID-19 Confirmed Cases (-3)	-0.044	0.079	-0.552	0.581
COVID-19 Confirmed Cases (-4)	-0.213	0.049	-4.370	0.000
Investor Sentiment	89.215	21.556	4.139	0.000
Investor Sentiment (-1)	-33.227	22.443	-1.481	0.140
Investor Sentiment (-2)	-29.092	20.804	-1.398	0.163
Market Index Return	-12859.190	3445.062	-3.733	0.000
Trading Volume	37.958	44.592	0.851	0.395
Turnover Rate	-10884.950	12257.450	-0.888	0.375
Volatility	31.555	36.395	0.867	0.387
Volatility (-1)	-99.780	51.959	-1.920	0.056
Volatility (-2)	53.066	51.601	1.028	0.304
Volatility (-3)	171.997	51.916	3.313	0.001
Volatility (-4)	-131.036	34.707	-3.775	0.000
COVID-19 Vaccination	0.111	0.056	1.992	0.047
C	-1236.544	1072.295	-1.153	0.250
R-squared	1.000	Mean dependent var		146055.400
Adjusted R-squared	1.000	S.D. dependent var		64307.440
S.E. of regression	727.454	Akaike info criterion		16.060
Sum squared resid	195000000.000	Schwarz criterion		16.234
Log likelihood	-3082.584	Hannan-Quinn criteria		16.129
F-statistic	188017.900	Durbin-Watson stat		2.045
Prob (F-statistic)	0.000***			

Note: *p-value<.05, **p-value<.01, ***p-value<. 001.p-values and any subsequent tests do not account for model selection.

Table 7: The results of bound test (dependent variable: COVID-19 Confirmed Cases)

F-Bounds Test	Null Hypothesis:	No levels relationship			
Test Statistic	**Value**	**k**	**Significant**	**I (0)**	**I (1)**
			Asymptotic: n=1000		
			10%	1.99	2.94
F-statistic	3.893947	6	5%	2.27	3.28
			2.50%	2.55	3.61
			1%	2.88	3.99
			Finite Sample: n=80		
			10%	2.088	3.103
Actual Sample Size	386		5%	2.431	3.518
			1%	3.173	4.485

Table 8: ARDL error correction regression (dependent variable: COVID-19 Confirmed Cases)

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
D (COVID-19 Confirmed Cases (-1))	0.219	0.048	4.592	0.000
D (COVID-19 Confirmed Cases (-2))	0.257	0.047	5.498	0.000
D (COVID-19 Confirmed Cases (-3))	0.213	0.048	4.485	0.000
D (Investor Sentiment (-1))	89.215	18.229	4.894	0.000
D (Investor Sentiment (-2))	29.092	18.083	1.609	0.109
D (Volatility)	31.555	33.739	0.935	0.350
D (Volatility (-1))	-94.027	33.913	-2.773	0.006
D (Volatility (-2))	-40.961	34.013	-1.204	0.229
D (Volatility (-3))	131.036	33.831	3.873	0.000
CointEq (-1) *	-0.002	0.000	-5.634	0.000
R-squared	0.545	Mean dependent var		441.314
Adjusted R-squared	0.534	S.D. dependent var		1055.290
S.E. of regression	720.650	Akaike info criterion		16.024
Sum squared resid	1.95E+08	Schwarz criterion		16.126
Log likelihood	-3082.584	Hannan-Quinn criteria.		16.064
F-statistic	27.249	Durbin-Watson stat		2.045
Prob (F-statistic)	0.000***			

Note: *p-value<.05, **p-value<.01, ***p-value<. 001.p-values and any subsequent tests do not account for model selection.

When build the ARDL model with the dependent variable investor sentiment and select the optimal model as ARDL (4, 3, 0, 3, 1, 0, 0), as shown in Table 9. As shown in Table 10, the F statistic value is greater than the upper bound value at each significance level, so there seems a long-term cointegration relationship between investor sentiment and the other variables. Table 11 shows there is probably a significant short-term relationship among the variables.

Table 9: ARDL model selection (dependent Variable: investor sentiment)

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
Investor Sentiment (-1)	0.342	0.050	6.767	0.000
Investor Sentiment (-2)	-0.036	0.053	-0.675	0.500
Investor Sentiment (-3)	0.037	0.051	0.731	0.465
Investor Sentiment (-4)	0.126	0.048	2.638	0.009
COVID-19 Confirmed Cases	0.000	0.000	4.069	0.000
COVID-19 Confirmed Cases (-1)	-0.001	0.000	-3.171	0.002
COVID-19 Confirmed Cases (-2)	0.000	0.000	-1.100	0.272
COVID-19 Confirmed Cases (-3)	0.000	0.000	2.743	0.006
COVID-19 Vaccination	0.000	0.000	1.097	0.273
Market Index Return	47.372	7.558	6.268	0.000
Market Index Return (1)	27.619	7.807	3.538	0.001
Market Index Return (2)	10.162	7.961	1.277	0.203
Market Index Return (3)	26.826	7.792	3.443	0.001
Trading Volume	0.283	0.102	2.767	0.006
Trading Volume (-1)	-0.007	0.004	-1.744	0.082
Turnover Rate	-75.146	28.320	-2.653	0.008
Volatility	-0.003	0.020	-0.149	0.882
c	20.837	2.720	7.661	0.000
R-squared	0.395	Mean dependent var		40.789
Adjusted R-squared	0.367	S.D. dependent var		2.090
S.E. of regression	1.662	Akaike info criterion		3.900
Sum squared resid	1016.611	Schwarz criterion		4.084
Log likelihood	-734.610	Hannan-Quinn criteria		3.973
F-statistic	14.155	Durbin-Watson stat		2.059
Prob (F-statistic)	0.000***			

Note: *p-value<.05, **p-value<.01, ***p-value<. 001.p-values and any subsequent tests do not account for model selection.

Table 10: The results of bound test (dependent variable: investor sentiment)

F-Bounds Test	Null Hypothesis:	No levels relationship			
Test Statistic	**Value**	**k**	**Significant**	**I (0)**	**I (1)**
			Asymptotic: n=1000		
			10%	1.99	2.94
F-statistic	11.14988	6	5%	2.27	3.28
			2.50%	2.55	3.61
			1%	2.88	3.99
			Finite Sample: n=80		
			10%	2.088	3.103
Actual Sample Size	386		5%	2.431	3.518
			1%	3.173	4.485

Table 11: ARDL error correction regression (dependent variable: investor sentiment)

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
D (Investor Sentiment (-1))	-0.128	0.056	-2.294	0.022
D (Investor Sentiment (-2))	-0.163	0.049	-3.350	0.001
D (Investor Sentiment (-3))	-0.126	0.044	-2.866	0.004
D (COVID-19 Confirmed Cases)	0.000	0.000	4.280	0.000
D (COVID-19 Confirmed Cases (-1))	0.000	0.000	-1.057	0.291
D (COVID-19 Confirmed Cases (-2))	0.000	0.000	-2.907	0.004
D (Market Index Return)	47.372	6.666	7.106	0.000
D (Market Index Return (-1))	-36.988	10.051	-3.680	0.000
D (Market Index Return (-2))	-26.826	7.233	-3.709	0.000
D (Trading Volume)	0.283	0.029	9.889	0.000
CointEq (-1) *	-0.531	0.056	-9.534	0.000
R-squared	0.448	Mean dependent var		0.003
Adjusted R-squared	0.433	S.D. dependent var		2.187
S.E. of regression	1.647	Akaike info criterion		3.863
Sum squared resid	1.02E+03	Schwarz criterion		3.976
Log likelihood	-734.610	Hannan-Quinn criteria.		3.908
F-statistic	11.150	Durbin-Watson stat		2.059
Prob (F-statistic)	0.000***			

Note: *p-value<.05, **p-value<.01, ***p-value<. 001.p-values and any subsequent tests do not account for model selection.

Figure 1 shows the position diagram of the inverse root of the characteristic polynomial in the unit circle. If the modulus of all the roots is less than one and lie inside the unit circle, then the estimated VAR is stable. Based on the stable VAR model, certain results can be significant, such as impulse response and standard errors. Figure 1 indicates that all roots are in the unit circle, the VAR model selected in this study is stable.

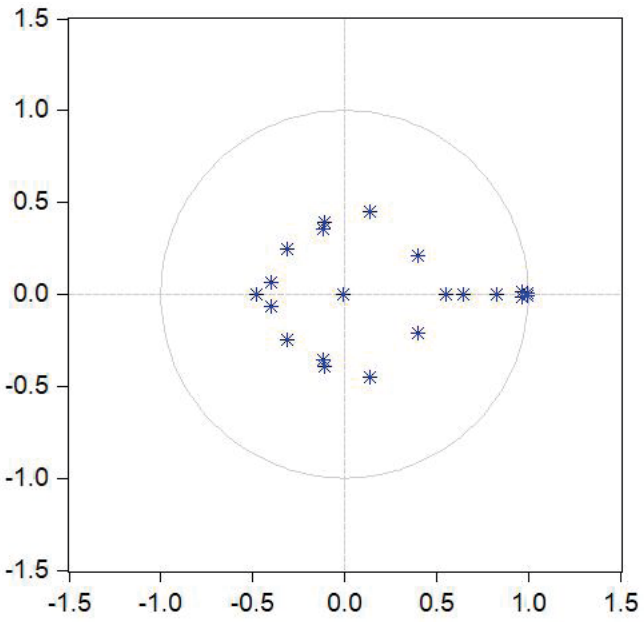

Figure 1: Inverse roots of AR characteristic polynomial

Table 12 presents the association among the variables based on the VAR method, as the results show that the stock market volatility has valid effect on investor sentiment. And the investor sentiment has significant effect on the turnover rate, trading volume, market index return, COVID-19 confirmed cases has significant effect on the market index return. Besides, the results statistically show that the stock market volatility has significant association with COVID-19 confirmed case that is interesting. Since COVID-19 is a human-related infectious disease, as the previous literature has proved market volatility can affect investor sentiment, and we also believe that this result is probably reasonable. Others correlation has not been found according to the results that has not been shown in the table.

Table 12: VAR Estimation Results

Variable	Estimate	Std. Error	t value	Pr(>|t|)
Volatility				
Investor Sentiment.l2	-8.484E-02	3.435E-02	-2.470	0.01396 *
COVID-19 Confirmed Cases.l3	-2.181E-04	6.985E-05	-3.122	0.00194 **
Adjusted R-squared:	0.9624	p-value < 2.2e-16***		
Investor Sentiment				
Turnover Rate.l1	-1.531E+02	7.636E+01	-2.005	0.04570 *
Trading Volume l1	5.512E-01	2.743E-01	2.009	0.04522 *
Market Index Return.l1	2.843E+01	8.443E+00	3.367	0.00084 ***
Market Index Return.l3	1.999E+01	8.493E+00	2.354	0.01909 *
Adjusted R-squared	0.254	p-value	< 2.2e-16***	
COVID-19 Confirmed Cases				
Market Index Return.l1	1.040E+04	3.669E+03	2.834	0.00485 **
Adjusted R-squared	0.9999	p-value	< 2.2e-16 ***	

Note: Group: All index, *** p < 0.001, ** p < 0.01, * p < 0.05, . p < 0.1

The table 13 shows both of max-eigenvalue test and trace test indicates 5 cointegrating equations at the 0.05 level, which seems there is long-term correlation among the variables and support the long-term association together with ARDL results.

Table 13: Results of Johansen Cointegration Test

Unrestricted Cointegration Rank Test (Trace)				
Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None *	0.343	398.034	125.615	0.000
At most 1 *	0.203	235.485	95.754	0.000
At most 2 *	0.174	147.706	69.819	0.000
At most 3 *	0.083	73.869	47.856	0.000
At most 4 *	0.069	40.157	29.797	0.002
At most 5	0.022	12.437	15.495	0.137
At most 6 *	0.010	3.954	3.841	0.047

Table 13: Results of Johansen Cointegration Test (Continue)

Unrestricted Cointegration Rank Test (Maximum Eigenvalue)				
Hypothesized No. of CE(s)	**Eigenvalue**	**Max-Eigen Statistic**	**0.05 Critical Value**	**Prob.****
None *	0.343	162.549	46.231	0.000
At most 1 *	0.203	87.778	40.078	0.000
At most 2 *	0.174	73.837	33.877	0.000
At most 3 *	0.083	33.713	27.584	0.007
At most 4 *	0.069	27.720	21.132	0.005
At most 5	0.022	8.483	14.265	0.332
At most 6 *	0.010	3.954	3.841	0.047

Note: * denotes rejection of the hypothesis at the 0.05 level **MacKinnon-Haug-Michelis (1999) p-values

Impulse response function reflects the dynamic influence of other variables in VAR model when one variable is affected by "exogenous shock". In the research, we will plot the impulse response analysis based on the dynamic changes of these variables over a period after this shock. The impulse response function is a conditional prediction, we estimate the values at different points after the impact. This study analysed the dynamic changes on COVID-19 confirmed cases, investor sentiment and COVID-19 vaccination after receiving impulse. It will observe the response from the independent variables including the stock market related variables in a certain time.

Figure 2 shows response of COVID-19 confirmed cases to COVID-19 vaccination using Cholesky (d.f. adjusted) factors, COVID-19 confirmed cases shows significant positive response to the COVID-19 vaccination, the effect persists over time, and seems increasing trend within a certain range, which indicates that there is possible long-term effect on COVID-19 confirmed cases.

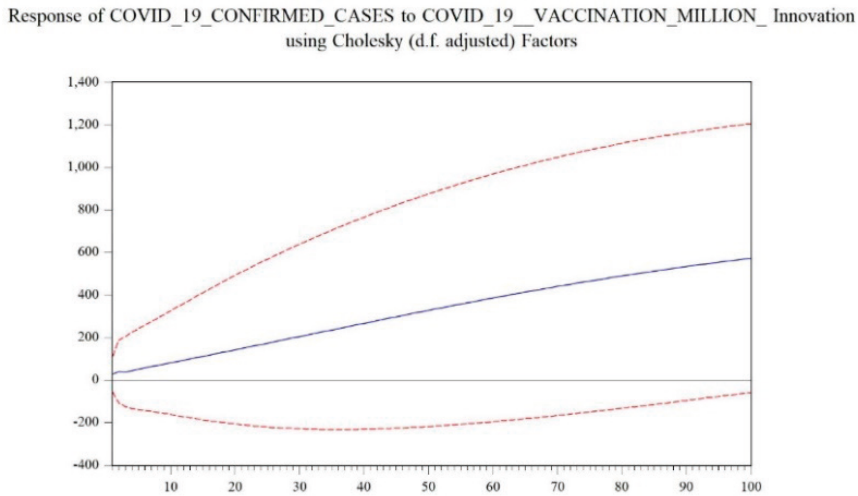

Figure 2: Impulse response from COVID-19 confirmed cases to vaccination

Figure 3 shows when receive the impulse from COVID-19 vaccination, investor sentiment shows a significant negative response when receive the impulse and the effect decrease even convergence to zero by the time.

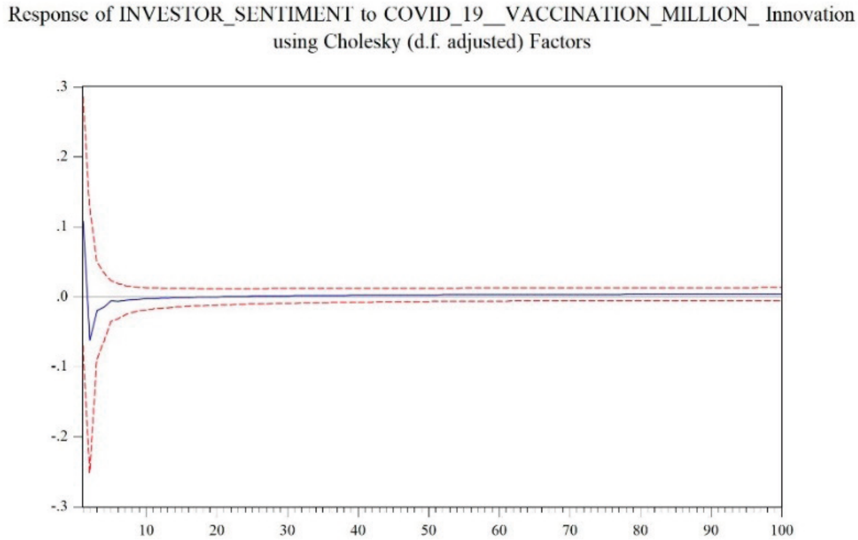

Figure 3: Impulse response from investor sentiment to COVID-19 vaccination

Figure 4 shows when receive the impulse from COVID-19 vaccination, how the stock market related variables response, market index return, trading volume, volatility, and turnover all show valid and immediate response to the shock from COVID-19 vaccination, but they all shows the trend of the effect decrease even convergence to zero by the time.

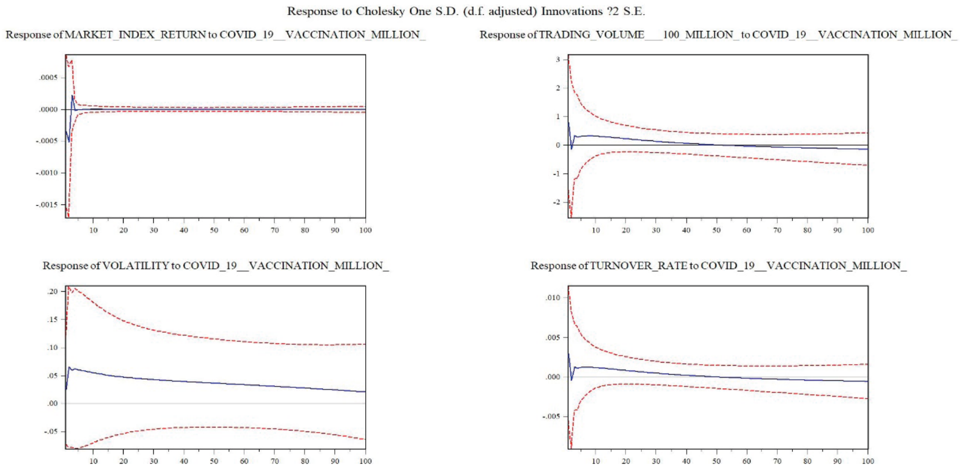

Figure 4: Impulse response from stock market variables to COVID-19 vaccination

When give a shock from the COVID-19 confirmed cases, the variables response as bellow, figure 5 shows COVID-19 vaccination received the shock from the COVID-19 that response negative effect immediately and significantly, the effect trend seems continuously increase in the study.

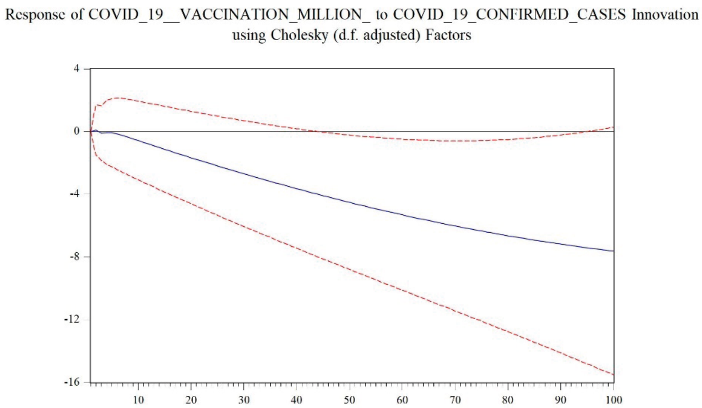

Figure 5: Impulse response from COVID-19 vaccination to COVID-19 confirmed cases

Figure 6 shows when receive the impulse from COVID-19 confirmed cases, investor sentiment shows a significant negative response when receive the impulse and the effect decrease even convergence to zero by the time.

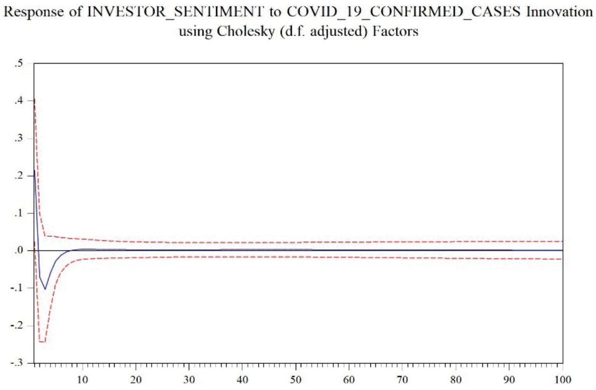

Figure 6: Impulse response from investor sentiment to COVID-19 confirmed cases

Figure 7 shows when receive the impulse from COVID-19 confirmed cases, how the stock market related variables response, market index return, trading volume, volatility, and turnover all show valid and immediate response to the shock from COVID-19 confirmed cases, trading volume, volatility, and turnover from positive effect cross to negative effect, and all converge with time in the study.

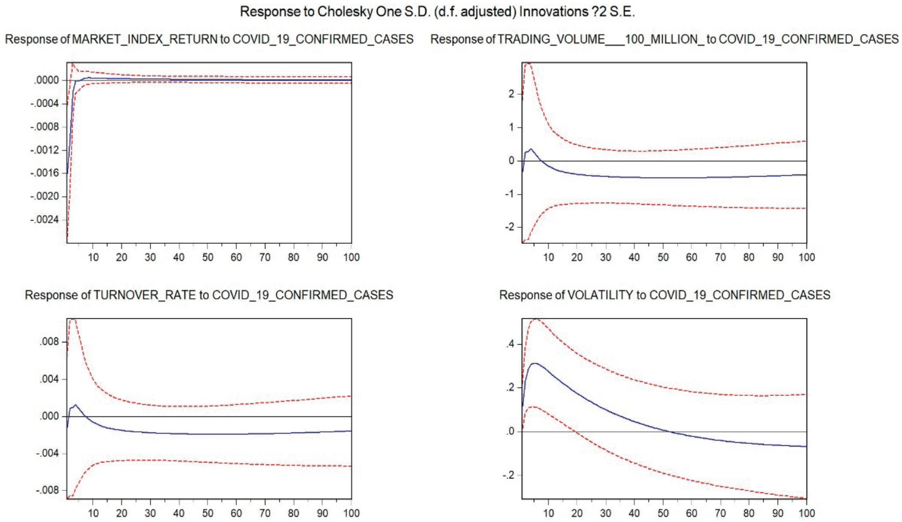

Figure 7: Impulse response from stock market variables to COVID-19 confirmed cases

Figure 8 shows the impulse responses from investor sentiment. Based on the results, COVID-19 vaccination indicates the negative response when received the shock from investor sentiment then cross to positive side, shows the possible long-term effect trend.

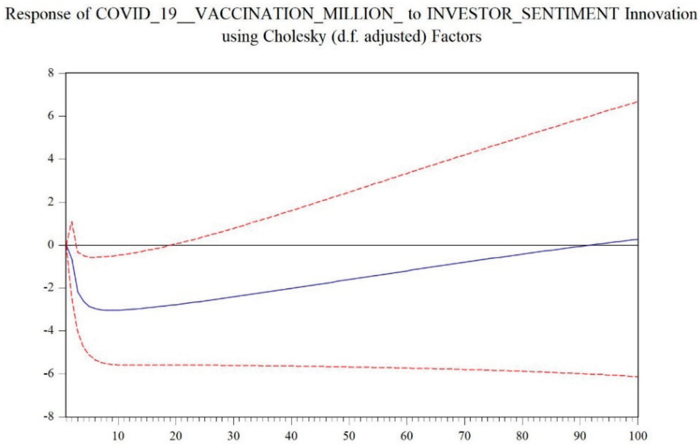

Figure 8: Impulse response from COVID-19 vaccination to investor sentiment

When the COVID-19 confirmed cases received the impulse from investor sentiment, it shows the significantly negative effects as Figure 9.

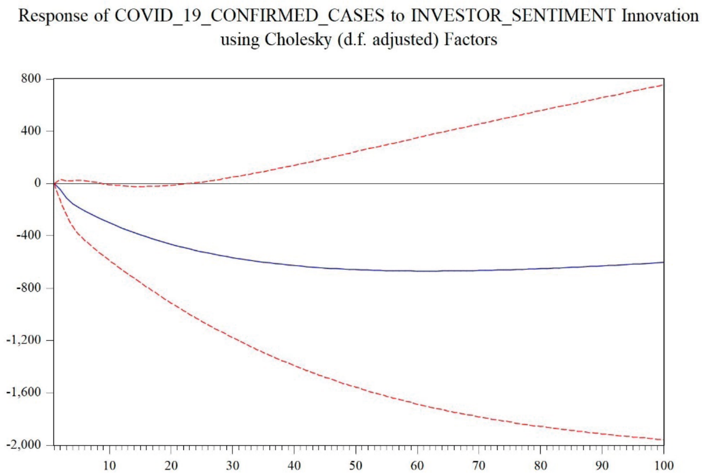

Figure 9: Impulse response from COVID-19 confirmed cases to investor sentiment

About the stock market related variable, when receive the impulse from the investor sentiment, as Figure 10 shows the market index return show significant response in the study, and response converge by the time. The trading volume, volatility, and the turnover rate show the significant response, but the effect decrease an converge over the time.

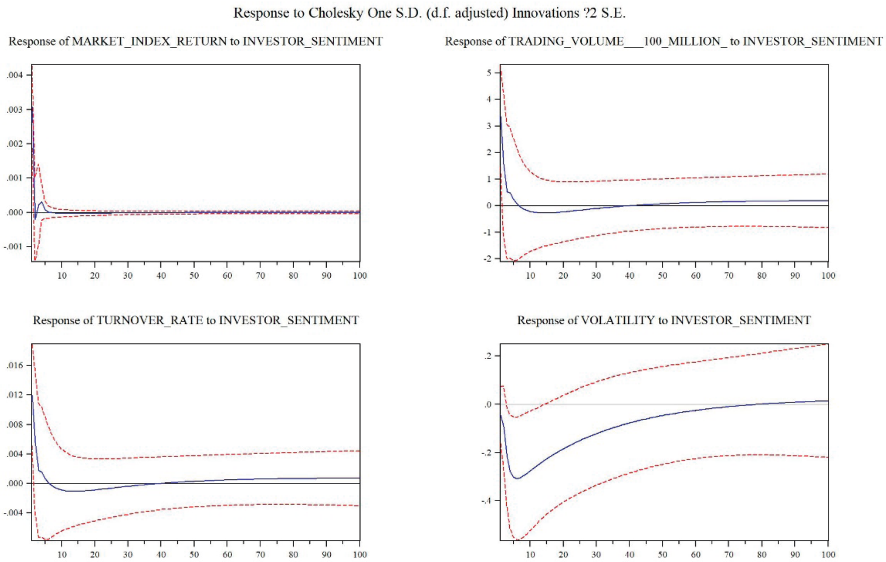

Figure 10: Impulse response from stock market related variables to investor sentiment

Variance decomposition is a statistical method utilized to examine the contribution of structural shocks that affect endogenous variables. As illustrated in Figure 11, COVID-19 vaccination, COVID-19 confirmed cases, investor sentiment, market index return, trading volume, turnover rate, and volatility exhibit the greatest influence on their respective outcomes. Additionally, our findings demonstrate that investor sentiment plays a substantial role in various factors, which shows the most contribution among the variables including COVID-19 vaccination, COVID-19 confirmed cases, and market-related variables, particularly COVID-19 vaccination, and market index return. Furthermore, COVID-19 confirmed cases has a significant contribute on investor sentiment, market volatility, and market index return.

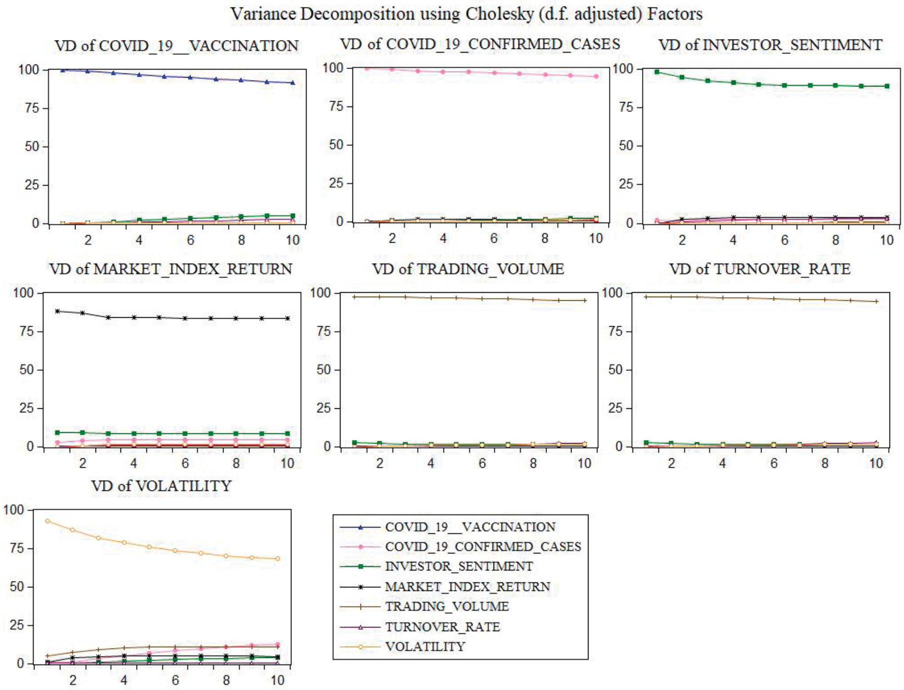

Figure 11: Results of Variance Decomposition

Conclusion

This study focuses on the interrelationships between PHEIC, vaccination, investor sentiment, and the stock market, which take the COVID-19 pandemic as a case study. Seven relevant variables, including COVID-19 cases, vaccination, investor sentiment, and stock market variables such as volatility, trading volume, market index return, and turnover rate, were selected for analysis using ARDL model, cointegration and VAR model. China as the first reported COVID-19 outbreak and first country to take policies to prevent the pandemic, which provide a good opportunity to get more knowledge on the pandemic.

Based on the results of ARDL model, it is found that when respectively use COVID-19 confirmed cases, COVID-19 vaccination, and investor sentiment as the dependent variables, there seems long-term and short-term association among the cases, vaccination, investor sentiment and stock market-related variables. The results of cointegration test, it is found that there seems long-term correlation among COVID-19 confirmed cases, vaccination, and stock market related variables, which is supportive to the results of ARDL model analysis.

VAR model estimation and impulse response analysis to dynamically explore the potential effects of these variables on each other. Specifically, by taking COVID-19, investor sentiment, and vaccination as the impulse variables, the study observes the response from the variables to test for possible effect among them. Refer to the VAR estimation, stock market volatility has valid effect on investor sentiment. And the investor sentiment has significant effect on the turnover rate, trading volume, market index return, which support the previous studies on investor sentiment impact on decision-making and stock market, and product some economy related consequence. Moreover, COVID-19 confirmed cases has significant effect on the market index return. Besides, the results statistically show that the stock market volatility has significant association with COVID-19 confirmed case since COVID-19 is a human-related infectious disease, as the previous literature has proved market volatility can affect investor sentiment, and we also believe that this result is probably reasonable.

According to the impulse response function analysis, COVID-19 confirmed cases shows significant positive response to the COVID-19 vaccination, the effect persists over time, and seems increasing trend within a certain range, which indicates that there is possible long-term effect on COVID-19 confirmed cases. Investor sentiment shows a significant negative response when receive the impulse and the effect decrease over time. Market index return, trading volume, volatility, and turnover all show valid and immediate response to the shock from COVID-19 vaccination, but they all shows the trend of the effect decrease by the time. When COVID-19 vaccination received the shock from the COVID-19 that response negative effect immediately and significantly, the effect trend seems continuously increase in the study. However, investor sentiment and stork market show significant response when receive but decrease even convergence to zero by the time. COVID-19 vaccination indicates the negative response when received the shock from investor sentiment then cross to positive side, shows the possible long-term effect trend. COVID-19 confirmed cases response the shock form investor sentiment as significantly negative effects. About the stock market related variable, when receive the impulse from the investor sentiment, the market index returns show significant response in the study, and response converge by the time. The trading volume, volatility, and the turnover rate show the significant response, and the effect shows decrease trend in the future.

Variance decomposition result shows that COVID-19 vaccination, COVID-19 confirmed cases, investor sentiment, market index return, trading volume, turnover rate, and volatility make the greatest contribution on their respective outcomes. And the findings demonstrate that investor sentiment plays a substantial role in various factors.COVID-19 confirmed cases has a significant contribute on investor sentiment, market volatility, and market index return.

Based on the significant long-term and short-term association among COVID-19, investor sentiment, vaccination, and the stock market. One of the important implications is effective controlling COVID-19 pandemic seems have an impact on both investor sentiment and the stock market. Second, according to a long-term co-integration relationship among variables, sustainable policy probably is necessary. Moreover, investor sentiment as an active variable is valuable to be considered not only the impactor mentioned in the study but the other affected variables such as: news, internet public opinion, open data. Meanwhile, investor sentiment has a significant response to COVID-19 vaccination, and public information on COVID-19 vaccination may help regulate investor sentiment, then effect on the investor-decision making. Information management is a kind of work that the policy makers would better practice. In the end, based on the results, when investor plan to make the investment decisions, the variables mentioned in the study could be referred.

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