





CO-INTEGRATION AMONG COVID-19, INVESTOR SENTIMENT, AND THE STOCK MARKET

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ABSTRACT

Article History

Received: 5 July 2022

Revised: 25 August 2022

Accepted: 9 September 2022

Published: 28 September 2022

Keywords

ARDL model
COVID-19
Decision-making
Investor sentiment
Risk-avoidance
Stock market.

This study focuses on stock market performance during the COVID-19 pandemic, aiming to research the co-integration among COVID-19 cases, investor sentiment, and the stock market. The data for the study comprised index returns, trading volume, turnover rate, and volatility from CSI300 index from January 2020 to December 2021. The paper planned to introduce methods that used the autoregressive distributed lag model, co-integration test, and error correction model to achieve the aims. The results show that there is a long-term co-integration relationship among these variables. However, when we consider the long-term association between COVID-19 and investor sentiment and individual stock market variables separately, we find no association among COVID-19 and market volatility, trading volume, or turnover rates. From the perspective of investor sentiment, there is no long-term relationship between investor sentiment and market volatility. Therefore, the model results show that there is a long-term relationship among the variables only when the data are integrated, but this relationship does not always persist when considering individual variables. As the COVID19 still continues, the study results would have the implications for the investment decision-making and risk avoidance to face the pandemic.

Contribution/Originality: This study identifies a long-term co-integration relationship among COVID-19, investor sentiment, and stock market when integrated. The results highlight the importance of analyzing multiple variables in investment decision-making, especially in times of heightened uncertainty generated during the COVID-19.

1. INTRODUCTION

Since the beginning of the 21st century, the World Health Organization (WHO) has classified six infectious disease pandemics as a Public Health Emergency of International Concern (PHEIC), with COVID-19 being the sixth and most recent. After initially declaring COVID-19 as a PHEIC, WHO declared that COVID-19 outbreak would still continue to constitute a PHEIC in order to bring focus to potentially global public health risks and call for the international community to coordinate and mobilize its resources to prevent spread of the disease and prepare for the economic burden the emergency will impose (Wilder-Smith & Osman, 2020). Currently, the pandemic's global spread continues to have severe economic and social impacts.

The stock market is a barometer of economy. Stock returns fluctuate with the economic cycle, and these fluctuations can lead to a recession in the real economy. The actual economy is linked to the stock market, which stimulates macroeconomic booms and busts, and vice versa (Westerhoff, 2012). The data on global markets indicate

there was a sharp drop around the first PHEIC declaration. During the outbreak of COVID-19, the American stock market fluctuated in the middle of February 2020, with the Dow Jones Industrial Average falling around 37 percent between 12th and 23rd February. Likewise, the S&P 500 index declined about 33 percent from 19th February to 23rd March, and the NASDAQ index dropped about 30 percent. From 9th March to 18th March 2020, the American stock market had four circuit breakers within ten days. On 18th March 2020, the American stock market declined after the circuit breaker resumed trading. The Dow Jones Industrial Average fell by nearly 11 percent in intraday trading. At one point, the NASDAQ was down nearly 9 percent. The S&P 500 was down almost 10 percent, especially within a short period of "PHEIC" declaration.

Similarly, within a short term after the outbreak, 3,188 stocks of China's two major stock markets, Shanghai Stock Exchange (SSE) and Shenzhen Stock Exchange (SZSE), fell by the daily limit on the first day of trading. With the SSE and SZSE index closing, especially after the day of the COVID-19 outbreak, the SSE index dropped about 11 percent and SZSE indexes around 14 percent, which were the most significant drop since 2015. This trend was similar to the global trend since the PHEIC declaration. However, during the remaining duration of the pandemic (until December 2021), performance showed a specific upward trend in both SSE and SZSE. The stock market index performance improved during this period of COVID-19 pandemic, if seen from a longer-term perspective. Likewise, S&P500, NASDAQ, and DJIA indexes too increased between January 2020 to December 2021. Based on these observations, a question arises to what extent COVID-19 affected stock markets.

In an attempt to understand the association between COVID-19 and stock markets, this study adopted a behavioral economics perspective. Emotions drives most significant decisions (Fiske, Gilbert, & Lindzey, 2010) while sentiment is positively correlated with stock returns realized in the short term (Seok, Hoon, & Doojin, 2017). The pandemic taught us that events may trigger positive or negative emotions that strongly influence investors' decision-making and corresponding stock market prices (Kowalewski & Śpiewanowski, 2020). In addition, the DRN's (disease-related news) has a positive and significant sentiment effect among investors on Wall Street (Donadelli, Kizys, & Riedel, 2017). WHO alerts and media news stories about dangerous infectious diseases also stimulated investor sentiment in such a way that triggered irrational trading. In examining such an impact, China's stock market provides an excellent sample to study from the perspective of behavioral economics. As Asia's biggest market and the second biggest market globally, China's stock market has the largest number of shareholders worldwide. Furthermore, retail investors account for more than 80% of its market value, and the leading institutions account for less than 20%. Thus, the Chinese stock market is very different from foreign stock markets, where institutional investors typically account for 70%–80% of market value.

The COVID-19 pandemic was a major historical event. Previous research has shown that big events affect the stock market and stock returns, such as mining disasters, sporting events, political events, and terrorist attacks (Chesney, Reshetar, & Karaman, 2011; Kowalewski & Śpiewanowski, 2020; Maillet & Michel, 2005; Shanaev & Ghimire, 2019). Current researchers have made some attempts to study the economic effects of the COVID-19 pandemic. Some researchers also studied the situation in China (Gao, Ren, & Umar, 2021; Huang, Zhao, & Wu, 2022; Ronaghi, Salimibeni, Naderkhani, & Mohammadi, 2022). However, there is still a lack of studies using economic models to analyze whether there is a long-term association between COVID-19 and the stock market.

Although there have been studies on the impact of COVID-19 on China's stock market from the perspective of behavioral economics, During the pandemic, volatility in stock returns was influenced by sentiment and could not be explained by economic losses alone (Sun, Wu, Zeng, & Peng, 2021). The overreaction in the Chinese stock market is mainly driven by industries and stocks that respond positively to lockdown measures, and the overreaction will be more intense (Huo & Qiu, 2020). This risk is exacerbated by fear, particularly over the impact of COVID-19 (Liu, Huynh, & Dai, 2021). Based on the benefits of effective measures taken by the Chinese government, the spread of COVID-19 has been curbed and investors' confidence in the stock market has been restored (Khan et al., 2020).

However, there are few studies (either short or long term) on China's stock market that incorporate investor sentiment into economic models to explore the association among COVID-19, investor sentiment, and stock markets.

To fill this research gap, the current study utilized data on COVID-19 in China, from the China Investor Sentiment Index (CISI), to study stock market variables (namely market index return, trading volume, turnover rate, and volatility of the CSI 300 index). The CISI is used to obtain quantitative psychological data on investor sentiment. This study employed the autoregressive distributed lag (ARDL) model, which can be used to determine whether there is a long-term dynamic association among variables. The ARDL model allows for a comprehensive analysis of the impact of COVID-19 on stock market performance and fully demonstrates causality. It is hoped the results can provide insights for any future stock market or investment risk caused by COVID-19 (or other pandemics). In summary, the study addressed the following research questions: Is there a statistical association between COVID-19 and the stock market? Did investor sentiment statistically impact the stock market over the course of the COVID-19 outbreak?

2. LITERATURE REVIEW

2.1. Financial Theories and Stock Markets

There has been a huge body of research on traditional finance and the stock market (Hamid, Suleman, Tahir, Syed, & Akash, 2010; Hu, Valera, & Oxley, 2019; Šonje, Alajbeg, & Bubaš, 2011). The stock market cannot be continuously efficient; it moves from an inefficient to an efficient state and vice versa (Munir, Ching, Furouka, & Mansur, 2012). As research progressed, we came across an increasing number of studies that identified apparently abnormal or irrational phenomena in markets, thus research started to focus on the role of individual behaviors (Tiwari, Aye, & Gupta, 2019; Tversky & Kahneman, 1992). In this way, researchers began to integrate psychology into finance (Gregoriou, Healy, & Le, 2019; Zhang, Zhang, & Hao, 2018). For example, about regretful investors and risk-averse investors, it was found that when equity premiums were low, they held more shares, and when the equity premiums were high, they held fewer shares. In conditions of uncertainty, regret drove an investor's decision-making away from extremes (Rocciolo, Gheno, & Brooks, 2019). Meanwhile, overconfident investors traded more in options than stocks (Bertella, Silva, & Stanley, 2020; De Bondt, 2020). In terms of cultural differences, individual investors in collectivist emerging economies were prone to behavioral biases which were usually more pronounced than among investors in developed, more individualistic countries (Tekçe & Yilmaz, 2015).

2.2. Investor Sentiment and Stock Markets

Many approaches in psychology attempt to explain sentiment impacts, such as fear, greed, and overconfidence, on behavior (Schwarz, 1990; Schwarz & Clore, 1983). Many psychologists have claimed that emotions are the main drivers of life's most significant decisions (Edmans, Garcia, & Norli, 2007; Fiske et al., 2010). In the context of risk estimation, events that affect emotions have global and specific priming effects (Constans & Mathews, 1993). Happy emotions may sometimes be associated with greater information processing activities; people with positive feelings focus on the hedonic consequences of their actions than people with neutral or negative emotions (Wegener, Petty, & Klein, 1994). Internal and external cues about benign or problematic situations have cognitive and motivational repercussions. Emotions guide individuals to make decisions that avoid inducing negative emotions (such as guilt and regret) and promote positive emotions (such as pride and happiness) (Lucey & Dowling, 2005; Morris, 2000). Furthermore, sentiment has a crucial role in decision-making under risk and uncertainty (Nareswari, Balqista, & Negoro, 2021).

Behavioral finance theory claims that investor sentiment has a significant influence on stock returns (Baker & Jeffrey, 2006; Baker & Wurgler, 2007; Schmeling, 2009). Significant events, such as tsunamis, epidemics, football matches, weather, etc., can impact investor sentiment (Buhagiar, Cortis, & Newall, 2018; Hood, Kamesaka, Nofsinger, & Tamura, 2013). Thus, stock price and risk-return tradeoff models should integrate investor sentiment and give it

a central role (Bathia & Bredin, 2018). There is a significant positive correlation between investor trading behavior, investor sentiment, and excess stock market returns (Yang & Zhou, 2015). Sentiment has positive correlation with stock returns realized in the short term based on the Korean stock market (Seok et al., 2017; Seok, Cho, & Ryu, 2019).

2.3. COVID-19, Investor Sentiment and Stock Market

In March 2020, the shock of COVID-19 caused one of the biggest stock market crashes in history. Stock market circuit breakers were triggered in many countries in a short space of time. COVID-19 became a serious impediment to financial markets, bringing about unexpected uncertainty and high volatility. The situation deteriorated rapidly as COVID-19 spread from country to country, with increasing panic levels in markets (Ali, Alam, & Rizvi, 2020). The great uncertainty of the pandemic and its associated economic losses have caused markets to become highly volatile and unpredictable (Zhang, Hu, & Ji, 2020).

Unsurprisingly, risk aversion was widespread among the increasingly connected, advanced and emerging stock markets, indicating that risk aversion in emerging market has become an essential contributor to highly connected international markets after the COVID-19 outbreak (Fassas, 2020). The COVID-19 pandemic led to a media frenzy, with extreme panic in the news media linked to increasing volatility in stock markets and even higher volatility in sectors most affected by the outbreak (Haroon & Rizvi, 2020). Panel data analysis of listed companies during the pandemic shows that daily new confirmed cases were negatively correlated with the stock returns of listed companies on that day (Al-Awadhi, Alsaifi, Al-Awadhi, & Alhammadi, 2020). Another study analyzed the mechanism on the short-term impact of COVID-19 to the stock market and found that investors' expectations and mood fluctuations due to COVID-19 caused short-term changes in stock prices (Liu et al., 2021).

Increases in confirmed COVID-19 cases and deaths were closely linked to illiquidity and increased volatility in the US stock market, which appears to have been exacerbated by public fear and the imposition of restrictions and lockdowns (Baig, Hassan, Omair, & Syed, 2021). There was an unprecedented negative overreaction of investor sentiment towards commodities such as crude oil, gold, silver, and energy. It showed that COVID-19-related economic uncertainty severely impacted all commodities except gold that was still seen as a safe haven and proved a measure of how investor fear dominated commodity markets (Shaikh, 2021). In Chinese data, a COVID-19 fear index constructed using data from the Baidu Index found that conditional skewness was negatively responsive to increase in the daily total number of confirmed cases, suggesting that the pandemic increased the risk of a stock market crash (Sun et al., 2021). Moreover, fear exacerbated this risk, particularly the fear of COVID-19 (Liu et al., 2021). Thus, it seems that the outbreak of the COVID-19 pandemic had a significant negative impact on financial markets. The relevant literature also shows that the economic effects of COVID-19 possibly cannot be analyzed without looking at investor sentiment as one of the influence factors.

Based on data from China, the daily increase in the total amount of confirmed COVID-19 cases and the total number of deaths were found to have a significantly negative impact on stock returns for all companies and the overall stock index; the pandemic negatively impact on the stock market returns (Al-Awadhi et al., 2020). Stock markets' reactions to the COVID-19 pandemic were rapid and varied, depending on the severity of the outbreak; stock markets has negative correlation with increases of confirmed COVID-19 cases but weakly to increased deaths (Ashraf, 2020). Narayan (2020); Narayan, Devpura, and Wang (2020) also identified an impact of COVID-19 on the shock resistance of the Yen against the US dollar; the Yen became highly stable in the COVID-19 context. A decline (rise) in new COVID-19-related cases and deaths was typically correlated with improved (worsened) liquidity in emerging economies' stock markets; a decline in COVID-19-related cases and deaths also signalled reduced uncertainty and improved liquidity in stock markets (Haroon & Rizvi, 2020). With the development of the pandemic, stock markets in all five ASEAN countries showed a high degree of consistency with the Dow Jones Index. In the long term, emerging market economies should be a haven for sovereign funds seeking higher yields as they overcome the challenges of the COVID-19 crisis and global supply chain disruptions (Kamaludin, Sundarasan, & Ibrahim, 2021).

Additionally, G7 governments' anti-COVID-19 initiatives, including lockdowns, travel bans, and economic stimulus plans, had a positive impact on G7 stock markets, among which lockdown was the most effective in buffering against COVID-19 (Narayan, Phan, & Liu, 2021).

Thus, COVID-19 cases have an adverse effect on stock returns and increased volatility and trading volume; however, in emerging markets, stock returns and volatility were affected but not trading volume (Harjoto, Rossi, Lee, & Sergi, 2021). Uncertainty had a small negative impact on the US stock market, and stock returns reacted relatively symmetrically to the fluctuations of COVID-19 cases in the US (Contessi & De Pace, 2021; Xu, 2021). In summary, the COVID-19 pandemic posed great uncertainties to the world economy. As it slowed down global economic activities and international economic and trade cooperation, which still continues, the impact of the globally spread COVID-19 on the world's real economy was still visible.

3. DATA AND METHODOLOGY

3.1. Data

This study used stock market data statistics relating to the COVID-19 pandemic, taken from the Wind Database (Wind Information Co., Ltd). The data was related to the CSI300 index and included volatility, index returns, trading volume, and turnover rate (Ausloos, Zhang, & Dhesi, 2020; Chu, Goodell, Li, & Zhang, 2021; Xu, Chen, Zhang, & Zhao, 2021). As for investor sentiment, the CISI was constructed by the National Development Institute of Peking University and Percent Point Company. Statistics on the number of daily confirmed COVID-19 cases were published by the National Health Commission of the People's Republic of China.¹ Thus, the study used six variables in total, and the sample interval was from January 2020 to December 2021, using daily data of 479 trading days. The analysis tools used in this study were Python 3.9 and E-views 11.

3.2. ARDL Model

The ARDL is a relatively new co-integration test method, which requires that the integrity of each time series is not more than 1, though it does not require that the time series' integrality be strictly I(0) or I(1) (Pesaran, Yongcheol, & Richard, 2001). The main function of the ARDL model is to determine whether there is a stable long-term relationship between variables based on bounds testing and estimating the correlation coefficient between variables on the premise of a co-integration relationship. Thus, we built our equations using the ARDL model to investigate the relationship between the COVID-19, investor sentiment, volatility, index returns, trading volume, and turnover rate.

The establishment of the co-integration test, from the perspective of measurement, meant that both the dependent variable and independent variable were unstable time series, but their linear combination was stable. Therefore, it was necessary to conduct a stationarity test as unit root test.

The unit root test is a random process problem. It defines a random sequence, $\{x_t\}$, $t = 1, 2, \dots$; it is a unit root process if $x_t = \rho x_{t-1} + \varepsilon_t$, $t = 1, 2, \dots$ where $|\rho| < 1$, $\{\varepsilon_t\}$ is a stationary sequence (white noise), and $E[\varepsilon_t] = 0$, $V(\varepsilon_t) = \sigma < \infty$, $Cov(\varepsilon_t, \varepsilon_s) = \mu < \infty$, here $T = 1, 2, \dots$. In particular, if $\rho = 1$, the above equation becomes a random walk sequence, which is the simplest unit root process. we can rewrite the definition as follows:

$$(1 - \rho L)x_t = \varepsilon_t, t = 1, 2, \dots \quad (1)$$

where L is lag operator, $1 - \rho L$ is a hysteretic operator polynomial and its characteristic equation $1 - \rho z = 0$ has root $z = 1/\rho$. When $\rho = 1$, the time series has a unit root, and $\{x_t\}$ is a unit root process. When $\rho < 1$, $\{x_t\}$ is a stationary sequence. When $\rho > 1$, $\{x_t\}$ is a non-stationary process with so-called explosive roots, which is still a

¹ The National Health Commission of the People's Republic is part of the State Council; its duty is to implement China's health strategies. This involves improving the people's health, preventing and controlling major diseases, coping with an aging population, developing related industry, and providing a comprehensive health service.

non-stationary process after differences, so it is not an integral process. In general, an integral process can be called a unit root process. If there is p order sequence correlation in y , it is corrected by p order autoregression:

$$y_t = a + \beta_1 y_{t-1} + \beta_2 y_{t-2} + \dots + \beta_p y_{t-p} + u_t \tag{2}$$

Where the time series y_t , y_{t-1} the first-order lag variable y_t , y_{t-2} the second-order lag variable of y_t . The maximum lag length in Equation 2 is p , which depends on the number of samples. u_t is the random disturbance term, and t is the time trend.

Subtract y_{t-1} from both ends of Equation 5, and, by adding and subtracting terms, obtain:

$$\Delta y_t = a + \gamma y_{t-1} + \sum_{i=1}^{p-1} \beta_i \Delta y_{t-1} + u_t \tag{3}$$

where:

$$\gamma = \sum_{i=1}^p \phi_i - 1, \beta_i = - \sum_{j=i+1}^p \phi_j$$

The Augmented Dickey–Fuller (ADF) test (Dickey & Fuller, 1979) method controls high-order sequence correlation by adding the lagged difference term of the dependent variable y_t to the right of the regression equation. Equations 4, 5 and 6 are three models of ADF, and the test sequence is from model (6) to model (5) to model (4). The principle of DF test and the corresponding ADF critical value distribution are used to test whether the null hypothesis of the model is valid. When the null hypothesis is rejected by the test, that is, the original sequence has no unit root and is stationary, the test can be stopped. Otherwise, continue validation until model (4) is validated.

$$\Delta y_t = \gamma y_{t-1} + \sum_{i=1}^{p-1} \beta_i \Delta y_{t-1} + u_t, \quad t = 1, 2, \dots, T \tag{4}$$

Where the time series is y_t , t is the time trend. $y_0 = 0$, γ is a real number and ε_t is an independent normal random variable with a sequence mean of zero and variance δ^2 [i.e., $\varepsilon_t \sim \text{NID}(0, \delta^2)$].

$$\Delta y_t = \gamma y_{t-1} + a + \sum_{i=1}^{p-1} \beta_i \Delta y_{t-1} + u_t, \quad t = 1, 2, \dots, T \tag{5}$$

Where a is the intercept item.

$$\Delta y_t = \gamma y_{t-1} + a + \delta t + \sum_{i=1}^{p-1} \beta_i \Delta y_{t-1} + u_t, \quad t = 1, 2, \dots, T \tag{6}$$

Where δt is the time trends.

Extending the definition will test:

$$\begin{cases} H_0: \gamma = 0 \\ H_0: \gamma < 0 \end{cases}$$

H_0 : There is at least one-unit root that exists.

The sequence y may also contain constant terms and time trend terms. By testing whether the estimated value $\hat{\gamma}$ of γ rejects the null hypothesis, the ADF method is used to test the unit root of variables.

The co-integration theory and method proposed by Engle and Granger (1987) provides another approach for non-stationary modeling sequences. There may be $k - 1$ linearly independent cointegration vector y_t whose dimension is k , and the cointegration variables share common trend components and are proportional in quantity. The cointegration test can be divided into two types according to the test objects: the first type is based on regression coefficients, such as the Johansen co-integration test (Johansen, 1988) the other is based on regression residuals, such as ADF tests.

The main inspection steps are as follows:

If k sequences y_{1t} and $y_{2t}, y_{3t}, \dots, y_{kt}$, are first-order unitary sequences, the regression equation is established as:

$$y_{1t} = \beta_1 + \beta_2 y_{2t} + \beta_3 y_{3t} + \dots + \beta_k y_{kt} + u_t \tag{7}$$

Where contains the k variable above, $y_{1t}, y_{2t}, y_{3t}, \dots, y_{kt}$ is $k \times 1$ vector and $\beta_1, \beta_2, \beta_3 \dots \beta_k$ is $k \times k$ coefficient matrix, u_t is a $k \times 1$ vector of random errors in white noise processes.

The residual estimated by the model is:

$$\hat{u}_t = y_{1t} - \hat{\beta}_1 - \hat{\beta}_2 y_{2t} - \hat{\beta}_3 y_{3t} - \dots - \hat{\beta}_k y_{kt} \tag{8}$$

Here, if the residual sequence is stable, it can be determined that there is a co-integration relationship between K variables $y_{1t}, y_{2t}, y_{3t}, \dots, y_{kt}$ in the regression equation, and the co-integration vector is $\hat{\beta}_1, \hat{\beta}_2, \hat{\beta}_3 \dots \hat{\beta}_k$.

Otherwise, there is no co-integration relationship between $y_{1t}, y_{2t}, y_{3t}, \dots, y_{kt}$.

The error correction model (ECM) is an econometric model in a specific form, whose main form was the DHSY model proposed by Davidson, Hendry, Srba, and Yeo (1978). Assume that the long-term equilibrium relationship between the two variables X and Y is:

$$Y_t = \alpha_0 + \alpha_1 X_t + \mu_t \tag{9}$$

It reflects the long-term equilibrium between X and Y .

Since X and Y are rarely at the equilibrium point in the real economy, what has actually been observed is only a short-term or unbalanced relationship between X and Y , assuming the following lagging form of distribution of order (1,1) :

$$y_t = \beta_0 + \beta_1 X_t + \beta_2 X_{t-1} + \mu Y_{t-1} + \varepsilon_t \tag{10}$$

The model shows that the value of Y in phase T is not only related to the change of X , but also to the state value of X and Y in phase $t - 1$.

Since variables may be non-stationary, the ordinary least squares (OLS) method cannot be directly used to properly transform the above-distributed lag model to obtain:

$$\begin{aligned} \Delta Y_t &= \beta_0 + \beta_1 \Delta X_t + (\beta_1 + \beta_2) X_{t-1} - (1 - \mu) Y_{t-1} + \varepsilon_t \\ &= \beta_1 \Delta X_t - (1 - \mu) \left(Y_{t-1} - \frac{\beta_0}{1 - \mu} - \frac{\beta_1 + \beta_2}{1 - \mu} X_{t-1} \right) + \varepsilon_t \end{aligned}$$

or
$$\Delta Y_t = \beta_1 \Delta X_t - \lambda (Y_{t-1} - \alpha_0 - \alpha_1 X_{t-1}) + \varepsilon_t \tag{11}$$

where:
$$\lambda = 1 - \mu \quad \alpha_0 = \frac{\beta_0}{1 - \mu} \quad \alpha_1 = \frac{\beta_1 + \beta_2}{1 - \mu}$$

If the parameter in (11) is regarded as equal to the corresponding parameter in $y_t = \alpha_0 + \alpha_1 X_t + \mu_t$, the item in parentheses in Equation 11 is the disequilibrium error term in the $t - 1$ phase. Equation 11 shows that the change of Y is determined by the change of X and the degree of disequilibrium in the previous period. Therefore, the value of Y has been corrected for the previous degree of disequilibrium.

Equation 11 $\Delta Y_t = \beta_1 \Delta X_t - \lambda(Y_{t-1} - \alpha_0 - \alpha_1 X_{t-1}) + \varepsilon_t$ is the first-order ECM, which can be written as:

$$\Delta Y_t = \beta_1 \Delta X_t - \lambda \text{ecm} + \varepsilon_t \tag{12}$$

where ecm represents the error correction term and is based on the distributed lag model Equation 10

Therefore, $|\mu| < 1$, $\lambda = 1 - \mu$ $0 < \lambda < 1$

At $t - 1$ phase, Y is greater than its long-term equilibrium solution $\alpha_0 + \alpha_1 X_t$, ecm is positive, then $-\lambda \text{ecm}$ is negative and ΔY_t decreases.

At $t - 1$ phase, Y is less than its long-term equilibrium solution $\alpha_0 + \alpha_1 X_t$, ecm is negative, then $-\lambda \text{ecm}$ is positive and ΔY_t increases.

Therefore, the following models are defined.

(1) Long-term equilibrium model:

$$y_t = \alpha_0 + \alpha_1 X_t + \mu_t \tag{13}$$

where α_1 can be regarded as the long-term elasticity of Y with respect to X .

(2) Short-term equilibrium model:

$$y_t = \beta_0 + \beta_1 X_t + \beta_2 X_{t-1} + \mu Y_{t-1} + \varepsilon_t \tag{14}$$

where β_1 can be regarded as the short-term elasticity of Y with respect to X

However, since the asymptotic distribution of the F statistic is non-standard, the threshold table of the usual standard F statistic cannot be referred to. Here, calculated the critical value table of F statistics corresponding to the number of different regression terms, which included a variety of situations such as whether the ARDL model included intercept terms and trend terms, and provided the corresponding critical value range for each type of model. A typical ARDL model structure is shown below:

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

Here:

$$\begin{aligned} \phi(L, p) &= 1 - \phi_1 L - \dots - \phi_p L^p \\ \beta_i(L, q_i) &= 1 - \beta_{i1} L - \dots - \beta_{iq_i} L^{q_i} \end{aligned} \tag{15}$$

where p represents the lag order of y_t , and q_i represents the lag order of x_{it} , the i th independent variable. L stands for hysteresis operator, defined as $L y_t = y_{t-1}$. 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.

4. RESULTS

The basic data of this study are shown in Table 1; the general statistics are used to describe or summarize the basic facts of observations. The ADF unit root test is used to conduct unit root tests on the variables and the test results are shown in Table 2.

Table 1. Descriptive statistics.

Variables	COVID-19 Confirmed Cases	Investor Sentiment	Market Index Return	Trading Volume	Turnover Rate	Volatility
Mean	86201.06	40.824	0.001	1.60E+10	0.578	19.704
Median	87331.00	40.900	0.001	1.49E+10	0.538	17.450
Maximum	102314.0	48.900	0.057	4.06E+10	1.472	38.010
Minimum	49.000	33.900	-0.079	7.74E+09	0.278	9.310
Std. Dev.	14901.67	2.175	0.014	4.92E+09	0.180	7.140
Skewness	-4.246	0.246	-0.638	1.343	1.342	0.986
Kurtosis	23.633	3.515	6.729	6.026	6.014	3.013
Jarque-Bera	9936.638	10.111	309.961	326.582	325.096	77.562
Probability	0.000***	0.006***	0.000***	0.000***	0.000***	0.000***
Sum	41290306	19554.90	0.213	7.67E+12	276.973	9438.100
Sum Sq. Dev.	1.06E+11	2261.524	0.083	1.16E+22	15.316	24363.51
Observations	479	479	479	479	479	479

Note: ***p-value<.001.

From the perspective of measurement, the establishment of the co-integration test means that both the dependent and independent variables are unstable time series, but their linear combination is stable. From the perspective of economics and finance, there is a long-term equilibrium relationship between the dependent and independent variables. This section uses the Johansen co-integration test to investigate the co-integration among COVID-19, investor sentiment index, index returns, trading volume, turnover rate, and volatility of the Chinese stock market to explain whether these variables have a long-term influence relationship. The results of the co-integration rank test are shown as Table 3. The minimum values of the five significant co-integration equations are determined, indicating a long-term correlation between the response variables and the stock market.

Based on the results shown in Table 2, i.e., that COVID-19 confirmed cases, investor sentiment index, 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 co-integration relationship among the variables. We selected the ARDL model containing only intercept terms through experiments, and the model constructed according to the Akaike information criterion is ARDL (4, 0, 1, 0, 0, 1), as shown in Table 4 and Figure 1. Based on the selected and constructed ARDL model, bounds testing was carried out. As shown in Table 5, the F statistic value is greater than the upper bound value at each significance level, so there is a long-term co-integration relationship between COVID-19 and the other variables in the study.

Akaike Information Criteria (top 20 models)

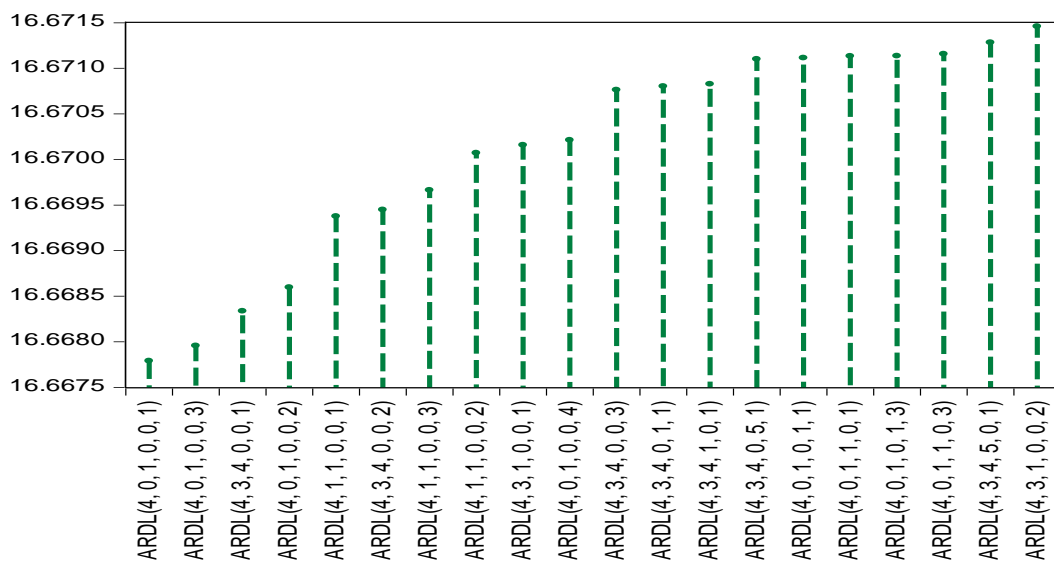


Figure 1. ARDL model selection summary (COVID-19 confirmed cases).

Table 2. Results of unit root test.

Variables	Order of integration	(C, T, K)	DW-statistic	ADF-statistic	1% level	5% level	10% level	P-value
COVID-19 Confirmed Cases	I (0)	(C, T, 1)	2.125	-8.691	-3.977	-3.419	-3.132	0.000***
Investor Sentiment	I (0)	(C, n, 1)	2.015	-9.885	-3.443	-2.867	-2.570	0.000***
Market Index Return	I (0)	(n, n, 1)	2.001	-14.818	-2.570	-1.941	-1.616	0.000***
Trading Volume	I (0)	(C, n, 1)	1.991	-4.723	-3.444	-2.867	-2.570	0.000***
Turnover Rate	I (0)	(C, n, 1)	1.990	-4.675	-3.444	-2.867	-2.570	0.000***
Volatility	I (1)	(n, n, 1)	2.001	-13.625	-2.570	-1.941	-1.616	0.000***

Note: ADF test type is (C, T, K), where C stands for intercept term, T stands for trend term, K stands for lag order, and *** stands for significance at 1% level.

Table 3. Results of uses Johansen co-integration test.

Test type: Unrestricted Co-integration Rank Test (Trace)				
Hypothesized No. of CE(s)	Eigenvalue	Trace Statistics	0.05 Critical Value	Prob.**
None *	0.452	444.344	103.847	0.000
At most 1 *	0.143	161.570	76.973	0.000
At most 2 *	0.068	88.802	54.079	0.000
At most 3 *	0.060	55.615	35.193	0.000
At most 4 *	0.035	26.303	20.262	0.007
At most 5 *	0.020	9.294	9.165	0.047
Test type: Unrestricted Co-integration Rank Test (Maximum Eigenvalue)				
Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	0.05 Critical Value	Prob.**
None *	0.452	282.747	40.957	0.000
At most 1 *	0.143	72.794	34.806	0.000
At most 2 *	0.068	33.187	28.588	0.012
At most 3 *	0.060	29.312	22.300	0.003
At most 4 *	0.035	17.009	15.892	0.033
At most 5 *	0.020	9.294	9.165	0.047

Note: Trace test indicates 6 co-integrating eqn(s) at the 0.05 level.
 Max-eigenvalue test indicates 6 co-integrating eqn(s) at the 0.05 level.
 * Denotes rejection of the hypothesis at the 0.05 level.
 **MacKinnon, Haug, and Michelis (1999) p-value.

Table 4. ARDL model selection (Dependent Variable: COVID-19 confirmed cases).

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
COVID-19 Confirmed Cases (-1)	1.034	0.043	24.260	0.000
COVID-19 Confirmed Cases (-2)	0.194	0.062	3.136	0.002
COVID-19 Confirmed Cases (-3)	-0.113	0.060	-1.863	0.063
COVID-19 Confirmed Cases (-4)	-0.136	0.040	-3.379	0.001
Investor Sentiment	116.381	26.047	4.468	0.000
Market Index Return	-12958.910	3845.772	-3.370	0.001
Market Index Return (-1)	-12543.820	3829.127	-3.276	0.001
Trading Volume	-4.61E-07	4.37E-07	-1.055560	0.292
Turnover Rate	12027.85	11994.41	1.003	0.317
Volatility	235.114	33.550	7.008	0.000
Volatility (-1)	-222.428	32.538	-6.836	0.000
C	-2706.264	1216.487	-2.225	0.027
R-squared	0.994	Mean dependent variable		86926.51
Adjusted R-squared	0.994	S.D. dependent variable		12679.85
S.E. of regression	999.377	Akaike info criterion		16.677
Sum squared residual	4.62E+08	Schwarz criterion		16.782
Log likelihood	-3948.807	Hannan-Quinn criterion		16.718
F-statistic	6894.647	Durbin-Watson statistic		2.013
Prob(F-statistic)	0.000***			

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

Table 5. The results of bound test (Dependent variable: COVID-19 confirmed cases).

F-Bounds Test	Null Hypothesis: No levels relationship			
Test Statistic	Value	k	Significance	I (0) I (1)
F-statistic	8.954261	5	Asymptotic: n=1000	
			10%	2.26 3.35
			5%	2.62 3.79
			2.5%	2.96 4.18
			1%	3.41 4.68
Actual Sample Size	474	Finite Sample: n=80		
		10%	2.355 3.5	
		5%	2.787 4.015	
			1%	3.725 5.163

The study calculates the long-term and short-term coefficient estimates to investigate and analyze the specific coefficient relationships among variables. As can be seen from Table 6, there is a significant long-term relationship between COVID-19 and investor sentiment and index returns. However, there is no long-term relationship between trading volume, turnover rate, and volatility. Table 7 demonstrates a significant short-term association between COVID-19, the investor sentiment index, and the stock market.

Table 6. Long run coefficient (COVID-19 confirmed cases).

Variables	Coefficient	Std. Error	t-Statistic	Prob.
Investor Sentiment	5832.130	2069.687	2.818	0.005**
Market Index Return	-1278001.00	425515.80	-3.003	0.003**
Trading Volume	-2.31E-05	2.31E-05	-1.001	0.318
Turnover Rate	602743.00	631082.60	0.955	0.340
Volatility	635.705	438.312	1.450	0.148

Note: ** stands for significance at 5% level.
 EC = Covid 19 Confirmed Cases - (5832.1298* Investor Sentiment-1278000.7004* Market Index Return-0.0000* Trading Volume+602743.0438* Turnover Rate+635.7050* Volatility).

Table 7. Short run coefficient (COVID-19 confirmed cases).

Variables	Coefficient	Std. Error	t-Statistic	Prob.
C	-2706.264	314.230	-8.612	0.000
COVID-19 Confirmed Cases (-1)	0.054	0.041	1.326	0.186
COVID-19 Confirmed Cases (-2)	0.249	0.038	6.517	0.000
COVID-19 Confirmed Cases (-3)	0.136	0.039	3.493	0.001
D (Market Index Return)	-12958.910	2907.537	-4.457	0.000
D(Volatility)	235.114	30.862	7.618	0.000
CointEquation (-1)*	-0.020	0.002	-8.976	0.000
R-squared	0.436	Mean dependent variable		215.267
Adjusted R-squared	0.429	S.D. dependent variable		1315.16
S.E. of regression	994.024	Akaike info criterion		16.656
Sum squared residual	4.62E+08	Schwarz criterion		16.717
Log likelihood	-3948.807	Hannan-Quinn criterion		16.680
F-statistic	60.290	Durbin-Watson statistic		2.013
Prob(F-statistic)	0.000***			

Note: *p-value<.05, ***p-value<.001.

Akaike Information Criteria (top 20 models)

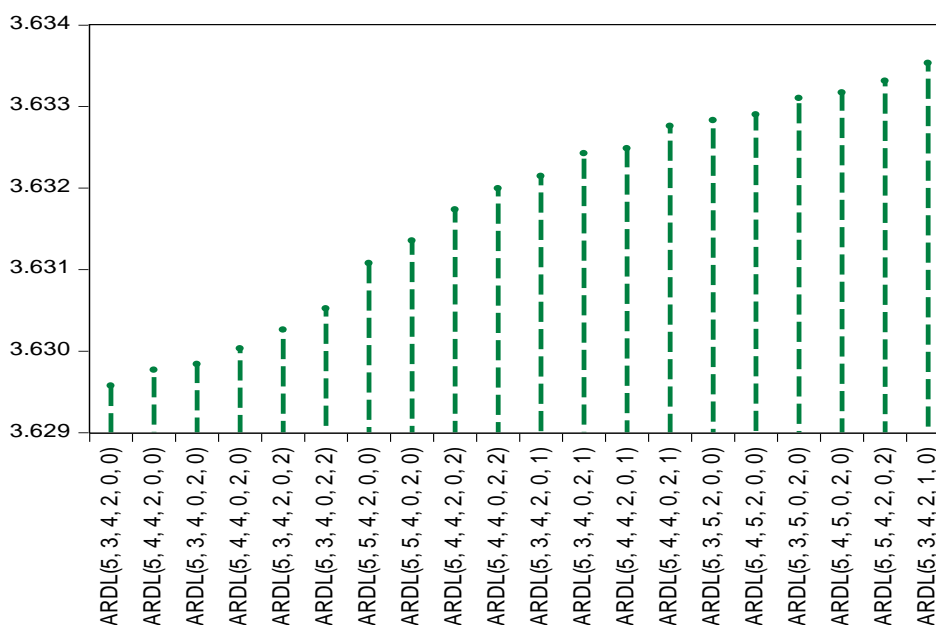


Figure 2. ARDL model selection summary (Investor sentiment).

To examine whether investor sentiment index is the dependent variable and whether other variables have a long-term association with it, we continued to build the ARDL model and selected the optimal model as ARDL (5, 3, 4, 2, 0, 0), as shown in Table 8 and Figure 2. As shown in Table 9, the F statistic value is greater than the upper bound value at each significance level, so there is a long-term co-integration relationship between investor sentiment and the other variables in this study. It can be seen from Table 10 that there is a significant long-term relationship between investor sentiment and COVID-19. When considering the long-term correlation with the stock market, there is a significant long-term relationship between investor sentiment and index returns, trading volume, and turnover rate but no long-term association between investor sentiment and stock market volatility. Table 11 shows there is a significant short-term relationship between investor sentiment and COVID-19 and the stock market.

Table 8. ARDL model selection (Dependent variable: Investor sentiment).

Variables	Coefficient	Std. Error	t-Statistic	Prob.*
Investor Sentiment (-1)	0.253	0.044	5.734	0.000
Investor Sentiment (-2)	0.013	0.046	0.286	0.775
Investor Sentiment (-3)	0.033	0.043	0.748	0.455
Investor Sentiment (-4)	-0.011	0.043	-0.256	0.798
Investor Sentiment (-5)	0.258	0.039	6.557	0.000
COVID-19 Confirmed Cases	0.000	6.35E-05	4.680	0.000
COVID-19 Confirmed Cases (-1)	-0.000	9.16E-05	-3.372	0.001
COVID-19 Confirmed Cases (-2)	-0.000	9.26E-05	-1.769	0.078
COVID-19 Confirmed Cases (-3)	0.000	6.19E-05	2.623	0.009
Market Index Return	41.988	5.320364	7.892	0.000
Market Index Return (-1)	42.096	5.706	7.378	0.000
Market Index Return (-2)	18.972	5.759	3.294	0.001
Market Index Return (-3)	14.186	5.698	2.490	0.013
Market Index Return (-4)	17.263	5.636	3.063	0.002
Trading Volume	1.58E-09	6.62E-10	2.389	0.017
Trading Volume (-2)	-5.13E-11	3.39E-11	-1.512	0.131
Trading Volume (-3)	-8.27E-11	2.93E-11	-2.824	0.005
Turnover Rate	-39.70473	18.279	-2.172	0.030
Volatility	-0.004	0.012	-0.310	0.756
C	19.402	2.585	7.505	0.000
R-squared	0.560	Mean dependent variable		40.790
Adjusted R-squared	0.542	S.D. dependent variable		2.149
S.E. of regression	1.455	Akaike info criterion		3.630
Sum squared residual	961.521	Schwarz criterion		3.805
Log likelihood	-840.209	Hannan-Quinn criterion		3.699
F-statistic	30.406	Durbin-Watson statistic		1.905
Prob(F-statistic)	0.000***			

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

Table 9. The results of bound test (Dependent Variable: Investor sentiment).

F-Bounds Test	Null Hypothesis: No levels relationship				
Test Statistic	Value	k	Significance	I (0)	
F-statistic	19.86439	5	Asymptotic: n=1000		
			10%	2.26	3.35
			5%	2.62	3.79
			3%	2.96	4.18
			1%	3.41	4.68
Actual Sample Size	474		Finite Sample: n=80		
			10%	2.355	3.5
			5%	2.787	4.015
			1%	3.725	5.163

Table 10. Long run coefficient (Investor sentiment).

Variables	Coefficient	Std. Error	t-Statistic	Prob.
COVID-19 Confirmed Cases	-2.93E-05	1.51E-05	-1.93568	0.054*
Market Index Return	296.436	38.820	7.6361	0.000***
Trading Volume	3.19E-09	1.38E-09	2.311	0.021**
Turnover Rate	-87.506	37.902	-2.309	0.021**
Volatility	-0.008	0.0256	-0.3139	0.754

Note: *** stands for significance at 1% level; ** stands for significance at 5% level; * stands for significance at 10% level
 EC = Investor Sentiment - (-0.0000*Covid 19 Confirmed Cases + 296.4361* Market Index Return +0.0000* Trading Volume - 87.5065*Turnover Rate - 0.0080* Volatility).

Table 11. Short run coefficient (Investor sentiment).

Variables	Coefficient	Std. Error	t-Statistic	Prob.
C	19.402	1.769	10.970	0.000
D (Investor Sentiment (-1))	-0.293	0.045	-6.580	0.000
D (Investor Sentiment (-2))	-0.280	0.040	-6.882	0.000
D (Investor Sentiment (-3))	-0.248	0.038	-6.458	0.000
D (Investor Sentiment (-4))	-0.259	0.037	-7.064	0.000
(COVID-19 Confirmed Cases)	0.000	5.84E-05	5.090	0.000
COVID-19 Confirmed Cases (-1)	1.61E-06	5.80E-05	0.028	0.978
COVID-19 Confirmed Cases (-2)	-0.000	5.99E-05	-2.710	0.007
D (Market Index Return)	41.988	4.940	8.500	0.000
D (Market Index Return (-1))	-50.420	10.527	-4.790	0.000
D (Market Index Return (-2))	-31.448	8.260	-3.808	0.000
D (Market Index Return (-3))	-17.263	5.560	-3.105	0.002
D (Trading Volume)	1.58E-09	1.30E-10	12.215	0.000
D (Trading Volume (-1))	8.27E-11	2.78E-11	2.971	0.003
CointEquation(-1)*	-0.454	0.041	-10.977	0.000
R-squared	0.521	Mean dependent variable		-0.003
Adjusted R-squared	0.506	S.D. dependent variable		2.060
S.E. of regression	1.447	Akaike info criterion		3.608
Sum squared residual	961.521	Schwarz criterion		3.740
Log likelihood	-840.209	Hannan-Quinn criterion		3.660
F-statistic	35.675	Durbin-Watson statistic		1.905
Prob(F-statistic)	0.000***			

Note: *p-value<.05, ***p-value<.001.

5. DISCUSSION AND CONCLUSION

This article used variables for COVID-19, investor sentiment, index returns, trading volume, turnover rate, and volatility and conducted a long-term co-integration analysis. It was found that when taking all the variables together, COVID-19, investor sentiment, and the stock market have a long-term co-integration relationship. Based on the ARDL model results, when COVID-19 was taken as the dependent variable, there was a significant long-term relationship between COVID-19 and market returns, which shows that market returns can be used as a reference for investment decision-making. However, no long-term relationship was identified between COVID-19 and trading volume, turnover rate, and volatility. These results show that there may be no long-term relationship between single stock market variables and COVID-19. Investors who rely only on a single variable for investment decision-making should take note of this result. Supposing they only focus on a single variable, such as volatility, this may lead them to believe that the COVID-19 pandemic has no long-term relationship with the stock market; this erroneous belief may result in investment losses. At a different time-scale, the ARDL model process provided evidence supporting the short-term relationship among the variables.

In addition, the results show that there is a significant long-term relationship between COVID-19 and investor sentiment, suggesting that COVID-19 has had a long-term impact on investor sentiment and decision-making. Thus, investor sentiment is likely to affect the market performance outcomes of investors' decisions. It also shows that investor sentiment can be used as a reference variable to guide investors' decision-making.

The results support prior research that identified a significant relationship between investor sentiment and the stock market (Baker & Jeffrey, 2006; Baker & Wurgler, 2007; Bathia & Bredin, 2018; Lan, Huang, & Yan, 2021; Nofsinger & Varma, 2013; Seok et al., 2019). However, this study adds a new contribution by studying the relationship between investor sentiment and the stock market during the COVID-19 pandemic. Based on the ARDL model, it identified a long-term co-integration relationship among COVID-19, investor sentiment, and the stock market. COVID-19 has a significant long-term relationship with investor sentiment when considering individual variables. In addition, index returns, trading volume, turnover rate, and investor sentiment have a significant long-term relationship.

However, there is no significant long-term relationship between volatility and investor sentiment. There may be some explanations for this. First, the COVID-19 outbreak has unique characteristics that differ from the contexts studied in prior research. Specific environments have different effects on investor sentiment. The present study's results show that COVID-19 significantly affects investor sentiment, which indicates that investor sentiment in the context of COVID-19 has environmental characteristics. Second, this may be because as time goes on, people begin to adapt to COVID-19 conditions. When the COVID-19 situation has stabilized, it no longer causes drastic swings in investor sentiment, explaining the non-significant result with respect to volatility. Third, COVID-19-related information may not have impacted investor sentiment to the extent that market volatility was affected.

In conclusion, in this study of COVID-19, investor sentiment, and the stock market, we found a significant short-term correlation between COVID-19 and the stock market, which is related to the economic impact of various intervention policies during COVID-19, such as lockdowns, quarantines, travel restrictions, etc. Due to the widely dispersed nature of the COVID-19 outbreak and the constant mutation of the virus, it is possible that new waves will continue to appear. The results about the short-term effect may provide some reference for short-term investment decisions. Secondly, the results on long-term effects show a significant long-term relationship between investor sentiment and the stock market. Thus, investor sentiment can be used as a reference index for investment decision-making.

5.1. Limitations

The data in this study are from China and cover the period from January 2020 to December 2021. Due to the fact that COVID-19 is ongoing, the data may be unable to fully summarize the situation. As the extent to which COVID-19 has been controlled varies in each country, the results can only be used as a reference and may not be generalized. COVID-19 represents a long-term dynamic change; if new COVID-19 strains appear or the number of confirmed cases increases in a short space of time, a new wave of the outbreak may occur, which may need to be continuously studied in real-time.

5.2. Future Research

Future research is required to track the relationship between COVID-19, investor sentiment, and the stock market, to see if their relationship reverses in the future and, if so, what is causing it. Second, the methods used in this study can be extended to a global scope, to examine the relationship between investor sentiment and the stock market using global data. We can also continue to study whether sporadic outbreaks of COVID-19 in cities where stock markets are located affects the performance of that stock market, by studying, for example, sporadic outbreaks in Shanghai or Shenzhen. It could be analyzed whether the widespread deployment of COVID-19 vaccines has affected the relationship between investor sentiment and the stock market and whether there is a connection between the number of COVID-19 vaccinations and investor sentiment or the stock market. Later research should continuously update the results presented here; the COVID-19 pandemic, investor sentiment, and stock market performance will continue to provide rich research materials.

Funding: This study received no specific financial support.

Competing Interests: The authors declare that they have no competing interests.

Authors' Contributions: Both authors contributed equally to the conception and design of the study.

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