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Half-life estimates of COVID19, Investor Sentiment, and the Stock Market

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Abstract

The half-life is used to estimate the adjustment speed of a variable to a new equilibrium point after being affected by the impulse response of a unit of shocks. The paper examines the adjustment speed of COVID19, investor sentiment, and the stock market through half-life estimates over the period from January 2020 to August 2022. To achieve the research goal, the study is based on the autoregressive model and the augmented Dickey-Fuller test results to estimate the half-lives of the variables. The results prove a valid short-term association and fast adjustment speed of COVID19, investor sentiment, and the stock market. The results of the estimates probably contribute to investor decision-making, risk avoidance, and policy proposals.

Keywords: COVID19, Half-life Estimates, Investor Sentiment, Stock Market
JEL Classifications: G10, G11, G41

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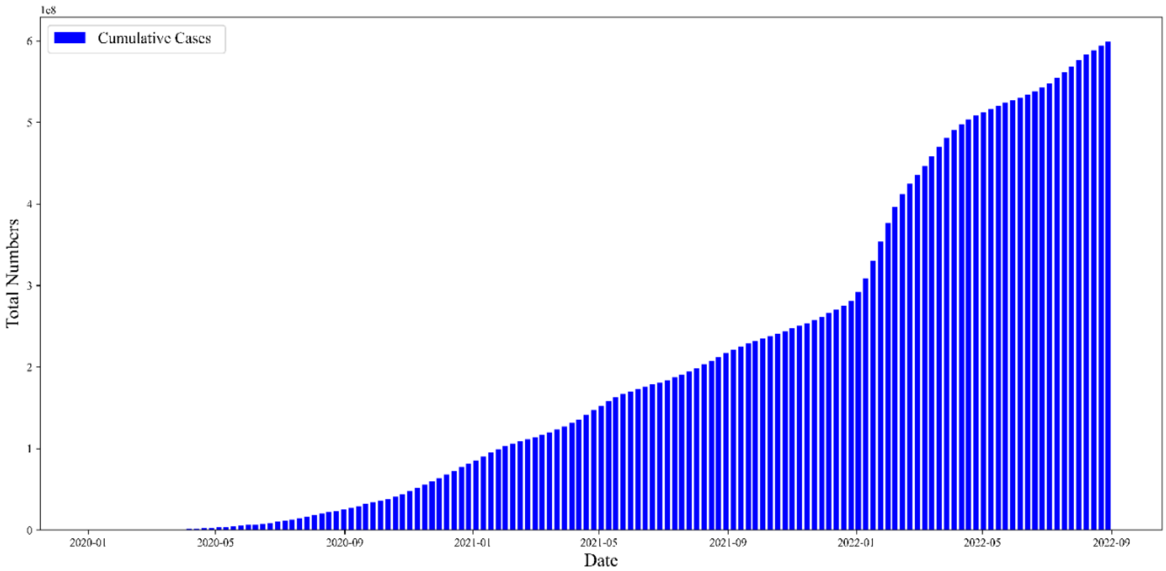
1. Introduction

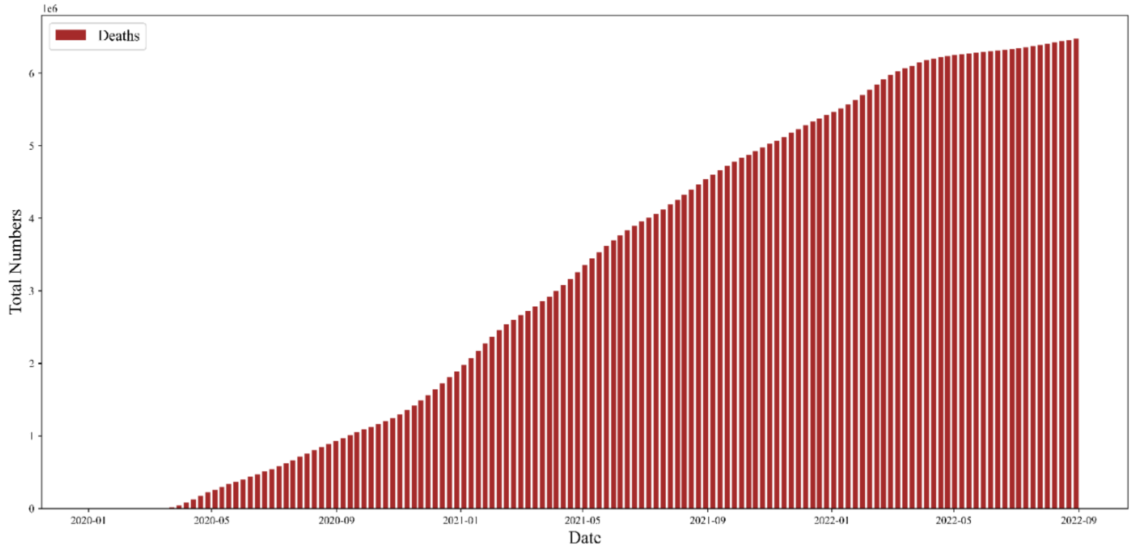
The COVID19 pandemic has become the most prominent of the six international public health emergencies of this century. Since the beginning of the 21st century, there have been six pandemics of infectious diseases as Public Health Emergency of International Concern (PHEIC), such as H1N1(2009), EBOV (2014), Poliomyelitis (2014), Zika (2016), EBOV (2018), and COVID19(2019). The COVID19 pandemic is continuing and changing the world. In particular, the pandemic harms global economies and stock markets (Ronaghi, Salimibeni, Naderkhani, & Mohammadi, 2022). Data on the COVID19 pandemic from the World Health Organization (WHO) show that up to 31st August 2022, around 598.97 million cumulative confirmed cases (as shown in Figure 1) and about 6.47 million deaths (as shown in Figure 2) had been reported. Both the confirmed and unconfirmed deaths showed a significant upward trend. In addition, the WHO has tracked the COVID19 outbreak and documented major events. Until now, the COVID19 has still been classified as a "PHEIC", which contains significant economic and societal potential threats. (As shown in Table 1).

Figure1: The Global COVID19 Cumulative Cases



Source:("Report of the global COVID19 cumulative comfirmed cases ", 2022)

Figure 2: The Global COVID19 Cumulative Deaths



Source:("Report of the global COVID19 cumulative deaths," 2022)

Table 1: The Global Interactions during the COVID19

Date	**Interactions**
11th January 2020	PRC. provides the genetic sequences of the novel coronavirus.
30th January 2020	The unknown coronavirus outbreak has been declared a PHEIC.
11th March 2020	COVID19 is characterized as a pandemic.
4th April 2020	Over 1 million cases of COVID19 confirmed worldwide.
5th October 2020	COVID19 pandemic has interrupted or stopped critical mental health services in 93% of the 130 countries covered, and the demand for mental health has been increasing.
14th January 2021	The COVID19 pandemic continues to constitute a PHEIC.
26th October 2021	The outbreak of COVID19 continued to constitute a PHEIC.
3rd November 2021	Issued its eighth emergency use listing for a COVID19 vaccine.
11th February 2022	First monoclonal antibody, tocilizumab, to treat COVID19.

Source:("Timeline: WHO's COVID19 response," 2022)

By comparison, the devastation of COVID19 to human health, wealth, and well-being has been greater than in World War II and other "PHEIC" around the world（as shown in Table 2）.

Table 2 Six PHEICs in the World since the 21st Century

Event	Outbreak time	PHEIC Period	Confirmed Cases
H1N1	March 2009	April-June 2009	> 50 million
Poliomyelitis	May 2014	May 2014 to present	525
EBOV (2014)	August 2014	August 2014 - March 2016	28,646
ZIKA	February 2016	February to November2016	>1.5 million
EBOV (2018)	June 2019	June 2019 to present	3421
COVID19	January 2020	January 2020 to present	>618million

Source:("Six PHEICs in the world since the 21st century," 2022)

Stock returns are influenced by systematic economic news, which is priced in line with their exposure(Chen, Roll, & Ross, 1986). The fundamental value of the stock market is related to national income; the real economy links to the stock market, which ultimately establishes a two-way feedback structure (Westerhoff, 2012). Global financial markets fell and fluctuated in response as the epicentre of the coronavirus moved from China to Europe and then to the United States. However, global markets have gone into free fall, especially in the later stages of the spread when China stabilized (Ali, Alam, & Rizvi, 2020).

The initial attack happened in China. Within a short term after the outbreak, stocks on the Shanghai (SSE) and Shenzhen stock exchanges (SZSE) fell by the daily limit on the first day of trading. Around the time that the WHO declared COVID19 as a PHEIC, the Shanghai Composite index fell from 2,943.29 to 2,746.61 from February 3 to March 9, and the Shenzhen Composite index also showed a significant decline, from 11,108.55 to 9,779.67, which shows how the economy reacted during the COVID19 outbreak through the stock market. During the COVID19 outbreak in 2019, China occupied approximately 16% of global GDP. China accounted for about 18 % of global GDP in 2022, making it the world's second-largest economic group. The share of manufacturing and services in GDP is 93%, which is higher than the 85 % during the SARS pandemic 20 years ago and showed an increased trend during the COVID19 pandemic. Beginning with the observations, it is unclear whether the current pandemic of COVID19 correlates with the economic consequence, whether the impact lasts, and how it adjusts, which raises a problem with explaining the economic phenomenon under the COVID19 situation. COVID19 is one of PHEICs, which is the longest current pandemic. China has achieved some results in pandemic prevention and control, which seems to have a certain role in explaining related economic phenomena such as stock market crisis caused by the pandemic and the policymaking and investment decision-making during the pandemic.

Current researchers have quickly begun to study the aspects of the COVID19 pandemic and its likely impact. The prolonged coronavirus pandemic is an important source of financial volatility that is challenging for risk management activities (Albulescu, 2020). Volatility is sensitive to COVID19 news, with negative news being more influential than positive ones(Baek, Mohanty, & Glambosky, 2020).During the COVID19 pandemic, natural gas, food, health care, and software stocks all posted big positive returns, while oil, real estate, entertainment, and hospitality stocks fell sharply (Mazur, Dang, & Vega, 2021). Excluding the number of confirmed cases reported in China, changes in the number of confirmed cases and deaths in the US had no impact on its stock market returns, which is based on data from the GARCH (1,1) model from April 8, 2019 to April 9, 2020(Onali, 2020). Lockdowns, travel bans, and economic stimulus packages had a positive impact on G7 stock markets. Among these, lockdowns were the most effective ones in mitigating the impact of COVID19 (Narayan, Phan, & Liu, 2021).

Research on the Chinese stock market related to COVID19 has been increasing. The COVID19 pandemic significantly impacted stock markets in China and other Asian countries. Investors coping with the pandemic reflected in stock price fluctuations due to traffic controls, software, and information technology services sectors have also benefited. However, the pandemic has adversely affected the transport, accommodation, and catering sectors. The COVID19 pandemic has hurt the share prices of the SSE while having a positive impact on the SZSE, and specifically, it has hit traditional industries more severely in China, while creating opportunities for the development of high-tech industries such as 5G network construction as well (He, Sun, Zhang, & Li, 2020). The impact of COVID19 on equity markets has shown significant leverage in both the US and China. COVID19 has a bigger impact on stock market volatility when it is more volatile. China remains highly sensitive to relatively small increases in daily new cases, and a loose monetary policy may be just a practical measure to stabilize fluctuations. Addressing public health issues as early as possible will not only reduce the damage caused by the impact of the pandemic and its attendant governance costs but also provide sufficient room for monetary policy to respond to uncertainties and potential risks that may arise in the near term (Gao, Ren, & Umar, 2021).The COVID19 pandemic was linked to a decline in the China Composite Index, and the impact varied by industry. Meanwhile, higher uncertainty due to COVID19 is significantly associated with greater volatility in stock returns on both composite and industry indexes(K. Liu, 2021).

Above all, there is a variety of research literature on the COVID19 pandemic and the stock market, including literature on China's COVID19 and the stock market. These works provide us with a good reference to understand the pandemic and the stock market. However, research it in different methodologies and different aspects seems to yield diverse results. According to the National Stock Market Investor Status Survey Report from China in February 2021, the number of stock investors in China break through 180 million, of which natural persons will account for 99.77%. Investor sentiment, as an important factor affecting investors' decision-making, Chinese data could provide us opportunity to study from behaviour finance perspective through adding investor sentiment to the research under the situation of COVID19. Although many studies have taken investor sentiment into account in stock market research and even discussed the association between investor sentiment and the stock market during the COVID19 pandemic, investor sentiment driven by COVID19- related news (CRNs) and economic-related announcements (ERAs) did not trigger irrational investment behavior in healthcare stocks in China, Hong Kong, South Korea, Japan, and the US, and both of them have a significant positive impact on healthcare portfolios (Sun, Bao, & Lu, 2021). Government policy reaction has a moderating effect on the relationship between sentiment and stock returns during the pandemic (Goel & Dash, 2021). Investor sentiment has significantly impacted Bitcoin returns during the COVID19 pandemic, and constructing a sentiment index can generate excess returns for investors using it as an earnings predictor (Bouteska, Mefteh-Wali, & Dang, 2022). However, discussions as intuitive as building the half-life estimates to reflect the adjustment speed are rare.

This paper plans to use quantitative indicators to build models, discuss the possible associations, and then adjust the speed when the COVID19, investor sentiment, and the stock market receive a shock. Dissimilarly, this paper uses the half-life estimates method to analyse the adjustment speed of the Chinese stock market, investor sentiment, and COVID19, which seems to provide a quantitative result that can be reflected in a more specific period on the basis of short-term association. It is expected to provide a probable practical reference for investors' investment decisions-making and the policymaker for the emotional guidance after the occurrence of PHEIC or a predictable base for the possible next wave of COVID19 outbreak.

The study is structured as follows: Section 2 is the literature review that reviewed the literature on investor sentiment, COVID19, and the stock market; Section 3 is data and methodology; Section 4 is the results of the analysis; conclusion and discussion is in Section 5; Section 6 is the limitations of the study; and the last section is the future research planning.

2. Literature review

Investor sentiment is defined as a concept based on psychological heuristics rather than Bayesian rationality, that is, a large number of investors make the same judgment errors, and their errors are interrelated phenomena(Barberis, Shleifer, & Vishny, 1998). Many psychologists recognize that emotions are the main drivers of life's most significant decisions (Edmans, Garc´ıa, & Norli, 2007;(Shefrin, 2002)). The sentiment takes a crucial position in decision-making under risk and uncertainty due to its interaction with cognitive assessment during decision-making. Such as when there is a high degree of complexity and uncertainty, emotions strongly influence decision (Nofsinger, 2005). The intuitive feelings experienced at the time of making a decision (often unrelated to the outcome) play a crucial role in the final choice (Lucey & Dowling, 2005). Internal and external cues to benign or problematic situations have cognitive and motivational repercussions (Schwarz & Clore, 2007). Overconfidence and representational heuristics have a significant impact on investors' decisions and stock market trading volume (Parveen, Satti, Subhan, & Jamil, 2020).

Sentiment is possible to measure. Sentiment volatility has a clear, effective, and regular impact on individual companies and the stock market, especially on stocks that are difficult to arbitrage or value (Baker & Wurgler, 2006, 2007). Descriptive and accurate models of prices and expected returns need to consider the significant role of investor sentiment, which is a negative predictor of total stock returns in all countries. In countries with poor market integrity and greater cultural susceptibility to herding and overreaction, market sentiment significantly impacts stock returns (Schmeling, 2009). Investor sentiment is an important factor in asset equilibrium prices and returns, and incorporating investor sentiment into asset pricing models can help explain the behavior of investors (Shu, 2010). There is a significant positive correlation between investor trading behavior, investor sentiment, and excess return on the stock market (Yang & Zhou, 2015). Emerging behavioral finance literature shows that investor sentiment has a significant impact on stock returns and leads to mispricing (Renault, 2017). Sentiment-induced buying and selling is an important determinant of stock price changes (Chau, Deesomsak, & Koutmos, 2016). Investor sentiment has a positive or negative impact on liquidity or illiquidity, and even foreign investor sentiment significantly affects liquidity in emerging stock markets (Debata, Dash, & Mahakud, 2018). Kumari (2019) also proved that investor sentiment plays a significant role in predicting stock market liquidity, and investors' past psychological bias and herd behavior are related to liquidity volatility through direct and indirect channels.

Investor sentiment should be regarded as a factor affecting asset prices, and fund managers should be advised to take investor sentiment valuation models into account when investing in this asset (Beer, Watfa, & Zouaoui, 2012). And sentiment is also proved to be able to be used to predict stock prices when stocks are closely watched by investors (Guo, Sun, & Qian, 2017). There is a significant relationship between investor sentiment and stock return fluctuation, which indicates that behavioral finance can significantly explain the behavior of stock returns in a certain region (Rupande, Muguto, & Muzindutsi, 2019). Through developing an investor sentiment index to capture investors' behavior using seven different indicators found under different multi-factor models, investors play a significant role in explaining the returns of most portfolios(Dhankar, 2019). In addition, fear heightens the risk of a stock market crash during the pandemic(Z. Liu, Huynh, & Dai, 2021).

The volatility of the stock market is reflected by a variety of factors, such as the opinions of other investors, analysts' forecasts, corporate news, extensive market coverage, and other financial news(Tetlock, 2014).The COVID19 pandemic has led to a media frenzy, with extreme panic in the news media linked to increasing volatility in the stock market and more volatility in the sectors most affected by the coronavirus outbreak (Haroon & Rizvi, 2020). The impact of COVID19 means the shock is permanent, based on the examination of the impact of the COVID19 crisis on Asian stock markets, including both the Kospi and the Shanghai Composite (Gil-Alana & Claudio-Quiroga, 2020). Besides, the COVID19 pandemic has a significant impact on the volatility of the U.S. stock market, which is sensitive to COVID19 news and has a negative bias due to the impact of specific economic indicator (Baek et al., 2020).

Risk in global financial markets has increased rapidly due to COVID19, and the response of individual stock markets is significantly correlated with the severity of the pandemic in each country. The great uncertainty of the pandemic and its associated economic losses have caused markets to become highly volatile and unpredictable (Zhang, Hua, & Ji, 2020). COVID19 had an unprecedented negative impact on the country's economic growth and the stock market. COVID19 cases have hurt equity returns and increased volatility, while only affecting those in emerging markets rather than developed markets (Harjoto, Rossi, Lee, & Sergi, 2021). The nature of the COVID19 crisis is different from that of the global financial crisis. During the global financial crisis, people's fears were mainly related to economic losses. However, during the COVID19 crisis, fear was strongly linked to health issues in addition to worries about the economic losses caused by the recession. Credit Suisse Fear Barometer (CSFB) and Volatility Index (VIX) helped predict currency and commodity volatility during the global financial crisis but not during the COVID19 crisis (Van Hoang & Syed, 2021). The outbreak of the COVID19 pandemic has a significant negative impact on financial markets, including energy stock markets, and as the call for clean energy continues to renew, investor focus theory suggests investors will pay more attention to the potential of investing in clean energy stocks (Wan, Xue, Linnenluecke, Tian, & Shan, 2021).

The proxies of positive and negative investor sentiment appear to be good predictors of stock returns and volatility during the COVID19 pandemic(Cevik, Altinkeski, Cevik, & Dibooglu, 2022). There is a double causal relationship between investor sentiment and the financial market index under optimistic or pessimistic circumstances, and the positive and negative returns of the financial market may have an impact on Chinese investor sentiment (Mezghani, Boujelbène, & Elbayar, 2021). Concerns about COVID19 have weighed heavily on the stock market, which stayed for a long time and did not quickly reverse (Harjoto, Rossi, & Paglia, 2021). The IPO companies act more sensitively to COVID19 related fears than similar existing companies do in the short term (Mazumder & Saha, 2021). Investor confidence in the government’s implemented support programmes is estimated through short-term abnormal return (Corbet, Hou, Hu, & Oxley, 2022). The long-term association between investor sentiment as represented by the crude oil volatility index and the West Texas Intermediate (WTI) crude oil futures price index has undergone structural changes caused by COVID19 (Huang & Zheng, 2020). The increasing number of COVID19 cases each day has adversely affected stock returns, with equity markets falling rapidly in response to the pandemic. In the initial stages of the outbreak, the market reacted negatively, and investor fear is the intermediary and transmission channel of the COVID19 impact on the stock market (Al-Qudah & Houcine, 2021). A decline in COVID19 related cases and deaths also signals reduced uncertainty and improved liquidity in stock markets (Haroon & Rizvi, 2020).

In the above literature, it is mentioned that sentiment affects decision-making and is correlated with stock market performance. Some of the research also indicates that the short-term association between investor sentiment and the stock market still exists during the COVID19 pandemic. However, few studies have quantified the term. The COVID19 outbreak, as well as the constant mutation of virus strains, sporadic outbreaks, and new outbreaks occurring randomly, have created great uncertainty for the world economy. How to strike a balance between promoting macroeconomic stability and preventing or controlling the pandemic has become a major economic and financial challenge. COVID19 is one of the major triggers of volatility in international financial markets, which may exacerbate instability in key financial markets and escalate systemic financial risks. While the COVID19 pandemic is dragging down global economic activities and international economic and trade cooperation, its impact on the world's real economy is also emerging.

Therefore, we intend to estimate the half-life of COVID19, investor sentiment, and stock market after certain shocks, so as to understand the adjustment speed of variables aftershocks. The discussion is based on quantitative data and seems to provide a reference for policy making, risk aversion, sentiment adjustment, and investment decision that are comparatively straightforward.

3. Data and methodology

3.1 Data

The database of the study includes the confirmed cases of COVID-19 collected from the National Health Commission of China (nhc.gov.cn), investor sentiment index refers to the National School of Development, Peking University, and stock market-related variables including market volatility, market index return, trading volume, and turnover rate of CSI300 collected from Wind Info. (Wind Information Co., Ltd), which is used to study the Chinese stock market (Ausloos, Zhang, & Dhesi, 2020; Qiao, Teng, Lia, & Liu, 2019; Xu & Pu, 2022; Zhou, Rao, & Lu, 2020). The period ranges from January 2020 to August 2022. The analysis tool used in this study is Python3.9 and E-Views 11.

3.2 Half-life Formula

Economists borrowed the concept of "half-life" from the natural sciences. In physics, the half-life of a radioactive isotope is the time it takes for its radioactive atoms in a sample to decay to half their original number. In economics, half-life is often used as a measure of the process time for the adjustment of a variable to a new equilibrium point after being affected by the impulse response of a unit of shocks. It is also used as a simple measure of the dynamics of time series (Morshed, K.Ahn, & Lee, 2006). This paper will discuss the association between COVID19, and investor sentiment as dependent variables, respectively, and further adapt half-life estimates to quantify the persistence of variable shocks. There are two ways to calculate the half-life. One is to treat the time series as a first-order autoregressive process AR(1), and the calculation is based on the first-order autoregressive coefficients(Zorzi, Rubaszek, & Mućk, 2013); the other is calculated using the regression parameters of the lag one phase in the ADF test (Christidou & Panagiotidis, 2010). This paper uses the two methods mentioned above to measure the half-life of variables.

Nelson and Plosser (1982) concluded that many economic time series are better expressed by unit root processes rather than deterministic time trends. Therefore, the unit root test is used to check the stability of variables in the time series analysis. If the unit root exists in the test series, then the series is non-stationary time series. Unit root refers to unit root process, and it has been proven that the presence of unit root process in the sequence will not be stable, which will lead to spurious regression in regression analysis. Before estimating the half-life of the variables, a stationarity test is developed.

Augmented dickey-Fuller Testing (ADF) is used in unit root testing methods to determine whether a sequence is stable by checking whether there is a unit root. The ADF test is the augmented DF. The DF test was proposed by (David A Dickey & Fuller, 1979). DF test formula is a first-order autoregressive process. In order to be suitable for the stability test of higher-order autoregressive processes, (David A. Dickey & Fuller, 1981; David A Dickey, Hasza, & Fuller, 1984) modified the DF test to some extent by introducing a higher-order lag term and the test regression formula of ADF . In this study, the ADF test as follows is used to obtain the coefficient:

The existence of P-order serial correlation in Y, which is corrected by P-order autoregressive process, leads to the following $AR(p)$model as:

$$y_t = b + a_1 y_{t-1} + a_2 y_{t-2} + a_p y_{t-p} + u_t \tag{1}$$

Subtract y_{t-1}, from both ends of (1), then obtain:

$$\Delta y_t = b + \rho y_{t-1} + \sum_{t-1}^{p-1} \emptyset_i \, \Delta y_{t-1} + u_t \tag{2}$$

Where u_t is white noise,

$$\rho = (\sum_{i=1}^{p} a_i) - 1$$
$$\emptyset_i = -\sum_{j=i+1}^{p} a_j$$

If the series Y contains constant terms and time trend terms, and the test is as follows:

(i) Autoregressive process without drift term：

$$\Delta y_t = \rho y_{t-1} + \sum_{i=1}^{p-1} \emptyset_i \, \Delta y_{t-1} + u_t, (t = 1,2, \ldots, T), y_0 = 0 \tag{3}$$

(ii) Autoregressive process with drift term:

$$\Delta y_t = b + \rho y_{t-1} + \sum_{i=1}^{p-1} \emptyset_i \, \Delta y_{t-1} + u_t, (t = 1,2, \ldots, T), y_0 = 0 \tag{4}$$

(iii) Autoregressive process with drift term and trend term:

$$\Delta y_t = b + \beta t + \rho y_{t-1} + \sum_{i=1}^{p-1} \emptyset_i \, \Delta y_{t-1} + u_t, (t = 1,2, \ldots, T), y_0 = 0 \tag{5}$$

Where b is the constant term, βt is the time trend term and u_t is the random disturbance term.

ADF test null hypothesis and alternative hypothesis are as follows:

$$\begin{Bmatrix} \mathrm{H_0}: \rho = 0 \\ \mathrm{H_1}: \rho < 0 \end{Bmatrix}$$

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

The statistic τ of ADF detection asymptotically follows the ADF distribution, If the null hypothesis $\mathrm{H_0}$ is not rejected, then there is at least one unit root that exists in y_t , that is, y_t is a non-stationary series. If the null hypothesis is rejected, y_t is a stationary series.

Then, determine the amount of optimal lag order in the model. This paper uses Akaike information criterion (AIC) and Schwarz criterion (SC) statistics to select the optimal lag order. In general, they can be expressed as:

$$AIC = \ln \frac{\sum \mathrm{e_t^2}}{\mathrm{n}} + \frac{2(k+1)}{\mathrm{n}} \tag{6}$$

$$\mathrm{SC} = \ln \frac{\sum \mathrm{e_t^2}}{\mathrm{n}} + \frac{k}{\mathrm{n}} \ln \mathrm{n} \tag{7}$$

Autoregressive model AR (1) builds as:

$$y_t = b + a y_{t-1} + u_t \qquad t = 1,2, \ldots, T \tag{8}$$

Characteristic equation: $\lambda - a = 0$

All roots fall inside the unit circle, and the AR (1) model is stationary with the basis for impulse response analysis *(*Campbell & Mankiw, 1987*)*, an American investment expert *(*Granville, 1960*)* revealed his latest invention, the moving average *(*MA*)*. Some researchers define the moving average *(*MA*)* coefficient as representing the process as an impulse response. The half-life based on the impulse response function has been verified by *(*Cheung & Lai, 2000; Choi, Mark, & Sul, 2004*)*. for a linear process*:*

$$y_t = \sum_{j=0}^{\infty} \beta_j \, \varepsilon_{t-j} \tag{9}$$

where $\beta_0 = 1$, ε_t is a random variable. The half-life in terms of $\square$ is $\beta_{\square} = 1/2$, This is the lag when the impulse response β_j becomes half of the initial impulse response.

Based on the econometric literature, the commonly used formula for the half-life of *(*stationary*)* time series y_t is*:*

$$\square = -\frac{\log 2}{\log \rho_1} \tag{10}$$

where ρ_1 is the autocorrelation of y_t at lag one, this formula is valid only when $\rho_1 > 0$, and is modified if y_t when AR *(*1*)* is satisfying*:*

$$y_t = \rho_1 y_{t-1} + \varepsilon_t \tag{11}$$

Therefore, when the sample size is n, the half-life of the AR *(*1*)* process is estimated by*:*

$$\square' = -\frac{\log 2}{\log \rho_1{}'} \tag{12}$$

For further studying the half-life of each variable, we continue to adapt the method of estimation. First, we calculate the values of the ADF for all variables. Then, based on the ADF test results for COVID19, investor sentiment, market index return, trading volume, turnover rate, and volatility can be rejected as null hypotheses, and on this basis, the rate of adjustment from the equilibrium level to the equilibrium level can be estimated：

$$\text{half} - \text{life} = \frac{\ln(0.5)}{\ln(1+\theta)} \quad (13)$$

Estimates the half-life by using the coefficient from a Dickey-Fuller test with one lag(Akram, 2003).

4. Results

The descriptive statistics are shown in Table 3, including 6 variables and 640 observations.

Table 3: Descriptive Statistics

Variables	COVID19 Confirmed Cases	Investor Sentiment	Market Index Return	Trading Volume (100 million)	Turnover Rate	Volatility
Mean	110306.20	40.9556	0.0001	153.7034	0.5538	19.8001
Median	90811.50	40.9000	0.0005	144.1727	0.5180	17.3700
Maximum	243449.00	48.9000	0.0567	406.0086	1.4719	38.0100
Minimum	49.00	33.9000	-0.0788	77.4481	0.2778	9.3100
Std. Dev.	51263.87	2.1872	0.0132	46.2335	0.1685	6.9468
Skewness	1.4810	0.2410	-0.5573	1.4677	1.4693	0.9692
Kurtosis	4.3238	3.3124	6.1304	6.7392	6.7215	2.8992
Jarque-Bera	280.7013	8.7982	294.4445	602.6044	599.5924	100.4674
Probability	0.0000***	0.0123**	0.0000***	0.0000***	0.0000***	0.0000***
Sum	70595946.00	26211.5900	0.0352	98370.1800	354.4221	12672.0500
Sum Sq. Dev.	1.68E+12	3056.7530	0.1108	1365884.0000	18.1392	30837.1700
Observations	640	640	640	640	640	640

*Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$*

Source: ("CSI300 index," 2020-2022)
("China investor sentiment index," 2020-2022)
("The latest situation of COVID19 pandemic in China," 2020-2022)

To ensure the stationarity of the time series, the unit test is used in this study, and the results show that the investor sentiment index, market index return, trading volume, and turnover rate are stable in the original series. The daily COVID19 confirmed cases are stable, and market volatility is stable in the first-order difference series. Their ADF test values are all less than the critical values of 1%, 5%, and 10%, and the corresponding P-values are all less than 0.0000. Therefore, the data were stable at the significance level of 1%. Based on the results, the AR model in this paper is built based on COVID19, investor sentiment, and market related variables.

Causality between dependent and independent variables may not occur simultaneously. There is usually a time lag in this process. The appropriate lag order should be selected before the AR model is established. In Table 5, the optimal lag order is selected jointly by the Chaike information criterion (AIC), the Schwarz information criterion (SC), and the Harman-Quinn information criterion (HQ).

Table 4: Results of Unit Root Test

Variables	**Order of integration**	**(C, T, K)**	**DW-statistic**	**ADF-statistic**	**1% level**	**5% level**	**10% level**	**P-value**
COVID19 Confirmed Cases	I (1)	(C, n,1)	2.1427	-9.5244	-3.4404	-2.8659	-2.5691	0.0000***
Investor Sentiment	I (0)	(C, n,1)	2.0174	-11.9930	-3.4404	-2.8659	-2.5691	0.0000***
Market Index Return	I (0)	(n, n,1)	1.9999	-17.6176	-2.5686	-1.9413	-1.6164	0.0000***
Trading Volume	I (0)	(C, n,1)	1.9945	-5.6065	-3.4404	-2.8659	-2.5691	0.0000***
Turnover Rate	I (0)	(C, n,1)	1.9943	-5.5232	-3.4404	-2.8659	-2.5691	0.0000***
Volatility	I (1)	(n, n,1)	1.9985	-15.1833	-2.5686	-1.9413	-1.6164	0.0000***

*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.*

Source: Author’s calculations.

Table 5: AR(p) Model Different Lag Orders of AR(p) Criterion Values
(dependent variable: COVID19)

Variable	**Investor Sentiment**				
	AR(p)	**AIC**	**SC**	**HQ**	**Prob.**
	AR (1)	17.10960	17.13752	17.12044	0.0000***
	AR (2)	16.98230	17.01720	16.99585	0.0000***
	AR (3)	16.94316*	16.98504*	16.95942*	0.0000***
	AR (4)	16.94571	16.99457	16.96467	0.0000***
	Market Index Return				
	AR (1)	17.10573	17.13365	17.11657	0.0000***
	AR (2)	16.96702	17.00192	16.98057	0.0000***
	AR (3)	16.92993*	16.9718*	16.94618*	0.0000***
	AR (4)	16.93209	16.98094	16.95105	0.0000***
	Trading Volume				
COVID19	AR (1)	17.13313	17.16105	17.14397	0.0000***
	AR (2)	17.01157	17.04647	17.02512	0.0000***
	AR (3)	16.97128*	17.01315*	16.98753*	0.0000***
	AR (4)	16.97305	17.02191	16.99201	0.0000***
	Turnover Rate				
	AR (1)	17.40819	17.43607	17.41901	0.0000***
	AR (2)	17.18014	17.21500	17.19367	0.0000***
	AR (3)	16.97125*	17.01313*	16.98751*	0.0000***
	AR (4)	16.97303	17.02189	16.99200	0.0000***
	Volatility				
	AR (1)	17.05978	17.08769	17.07061	0.0000***
	AR (2)	16.92125	16.95614	16.93479	0.0000***
	AR (3)	16.8874*	16.92927*	16.90365*	0.0000***
	AR (4)	16.88912	16.93798	16.90809	0.0000***

*Note: * stands for lag order selected by the criterion *** stands for significance at 1% level.*
AIC: Akaike information criterion
SC: Schwarz information criterion
HQ: Hannan-Quinn information criterion
Source: Author's calculations.

Based on the results of the lag order selection by the criterion, the best AR(p) model between the COVID19 and investor sentiment; the COVID19 and market index return; the COVID19 and trading volume; the COVID19 and turnover rate; the COVID19 and volatility is AR (3), which satisfied the autocorrelation (as shown in Table 5).

Table 6: AR(p) Model Different Lag Orders of AR(p) Criterion Values
(dependent variable: investor sentiment)

Variable	**COVID19**				
	AR(p)	**AIC**	**SC**	**HQ**	**Prob.**
	AR (1)	4.105307	4.133225	4.116144	0.0000***
	AR (2)	4.102597	4.137494	4.116143	0.0000***
	AR (3)	4.085248	4.127125	4.101503	0.0000***
	AR (4)	4.083131	4.131987	4.102096	0.0000***
	AR (5)	4.051792	4.107629	4.073467	0.0000***
	AR (6)	4.038356*	4.101171*	4.062739*	0.0000***
	AR (7)	4.040770	4.110565	4.067863	0.0000***
	Market Index Return				
	AR (1)	4.114062	4.141946	4.124885	0.0000***
	AR (2)	4.111279	4.146134	4.124808	0.0000***
	AR (3)	4.092082	4.133909	4.108317	0.0000***
	AR (4)	4.086583	4.135380	4.105523	0.0000***
	AR (5)	4.045052	4.100820	4.066699	0.0000***
	AR (6)	4.035091*	4.097831*	4.059444*	0.0000***
	AR (7)	4.037416	4.107127	4.064474	0.0000***
	Trading Volume				
	AR (1)	4.098628	4.126512	4.109451	0.0000***
	AR (2)	4.092663	4.127518	4.106192	0.0000***
Investor Sentiment	AR (3)	4.073211	4.115038	4.089446	0.0000***
	AR (4)	4.067315	4.116113	4.086256	0.0000***
	AR (5)	4.024460	4.080228	4.046106	0.0000***
	AR (6)	4.014967*	4.077706*	4.039319*	0.0000***
	AR (7)	4.017593	4.087303	4.044651	0.0000***
	Turnover Rate				
	AR (1)	4.099777	4.127662	4.110601	0.0000***
	AR (2)	4.093739	4.128594	4.107268	0.0000***
	AR (3)	4.074031	4.115858	4.090266	0.0000***
	AR (4)	4.068067	4.116865	4.087008	0.0000***
	AR (5)	4.025186	4.080954	4.046832	0.0000***
	AR (6)	4.015791*	4.078530*	4.040143*	0.0000***
	AR (7)	4.018426	4.088137	4.045484	0.0000***
	Volatility				
	AR (1)	4.129930	4.157848	4.140767	0.0000***
	AR (2)	4.127821	4.162719	4.141367	0.0000***
	AR (3)	4.108847	4.150724	4.125103	0.0000***
	AR (4)	4.105457	4.154314	4.124422	0.0000***
	AR (5)	4.068357	4.124193	4.090031	0.0000***
	AR (6)	4.053899*	4.116715*	4.078283*	0.0000***
	AR (7)	4.056619	4.126414	4.083711	0.0000***

*Note: * stands for lag order selected by the criterion   *** stands for significance at 1% level*
AIC: Akaike information criterion
SC: Schwarz information criterion
HQ: Hannan-Quinn information criterion

Source: Author’s calculations.

Based on the results of the lag order selection by the criterion that investor sentiment is the dependent variable, the best AR(p) model between investor sentiment and the COVID19; investor sentiment and market index return; investor sentiment and trading volume; investor sentiment and turnover rate; investor sentiment and volatility is AR (6), which satisfied the autocorrelation (as shown in Table 6).

In econometric literature, the half-life of (stationary) time series is often expressed by the formula $h = -\frac{\log 2}{\log \rho_1}$, where ρ_1 is y_t 's autocorrelation with one lag. This formula is valid only when $\rho_1 > 0$, and is modified if y_t when AR *(*1*)* is significant. Table 7 shows the results of the 1st-order autocorrelation coefficient of the variables, which is significant at the 1% level. Based on the valid results, the half-life of the variables will be estimated.

Table 7*:* 1st-order Autocorrelation Coefficient
*(*dependent variable*:* COVID19*)*

Variable	AR(p)	Coefficient	Std. Error	t-Statistic	Prob.
Investor Sentiment	AR (1)	0.407974	0.019088	21.372930	0.0000***
Market Index Return	AR (1)	0.418390	0.022233	18.818070	0.0000***
Trading Volume	AR (1)	0.412397	0.021518	19.165470	0.0000***
Turnover Rate	AR (1)	0.412303	0.021620	19.070640	0.0000***
Volatility	AR (1)	0.412748	0.021853	18.887660	0.0000***

*Note: *** stands for significance at 1% level.*
Source*:* Author's calculations.

Table 8*:* Half-Life Estimates
*(*dependent variable*:* COVID19*)*

Variable	Half-life(days)
Investor Sentiment	0.773126
Market Index Return	0.795494
Trading Volume	0.782537
Turnover Rate	0.782336
Volatility	0.783290

Note: Half-life is calculated by $-\frac{log(2)}{log(\rho)}$ *, where the coefficient is obtained from AR (1).*
Source*:* Author's calculations.

Table 8 displays the half-life estimates based on the AR (1). As the table shows, based on the COVID-19 analysis, the speed of the adjustment from the deviation toward equilibrium based on the COVID19 ranges from $0.77 < half - life < 0.80$. The half-life is now enormously reduced for investor sentiment and market-related variables. The results indicate that there is a short-term association among variables, and when investor sentiment receives a shock from COVID19, the adjustment speed is fast. And similarly, the market-related variables, including market index return, trading volume, turnover rate, and volatility, are also fast, which shows the variable can adjust within a short period after a shock.

The results of the 1st-order autocorrelation coefficient of the variables versus investor sentiment, which is significant at the 1% level *(*as shown in Table 9*)*.

Table 9: 1^{st}-order Autocorrelation Coefficient
(dependent variable: investor sentiment)

Variable	**AR(p)**	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
COVID19	AR (1)	0.486760	0.032868	14.80946	0.0000***
Market Index Return	AR (1)	0.483226	0.033677	14.34903	0.0000***
Trading Volume	AR (1)	0.516824	0.033790	15.29532	0.0000***
Turnover Rate	AR (1)	0.517524	0.033786	15.31761	0.0000***
Volatility	AR (1)	0.489720	0.033819	14.48074	0.0000***

*Note: *** stands for significance at 1% level.*
Source: Author's calculations.

Table 10: Half-Life Estimates
(dependent variable: investor sentiment)

Variable	Half-life(days)
COVID19	0.962726
Market Index Return	0.953080
Trading Volume	1.050139
Turnover Rate	1.052297
Volatility	0.970901

Note: Half-life is calculated by $-\frac{log(2)}{log(\rho)}$*, where the coefficient is obtained from AR (1)*
Source: Author's calculations.

Table 10 displays the half-life estimates based on the AR (1). As the table shows, the speed of the adjustment from the deviation toward equilibrium based on investor sentiment has been analysed, and ranges from $0.95 < \square alf - life < 1.05$. The results indicate that there is a short-term association among variables, and when the COVID19 received the shock, the adjustment speed was fast. The market-related variables also have a fast adjustment speed; among them is the market index return, and the volatility is comparatively fast. Comparing, when investor sentiment is the dependent variable, the adjustment speed is slightly slower than when exposed to shocks from COVID19, but overall, the adjustment speed response to both shocks is fast.

To further illustrate this situation, this study also takes the other approach by analysing the rate of adjustment of the deviation from equilibrium relative to COVID19 and investor sentiment indices and estimating their half-lives based on the coefficients of the Augmented Dickey-Fuller test. Table 11 shows the results of the Augmented Dickey-Fuller test on the variables, which can reject the null hypothesis of the unit root. The COVID19, investor sentiment, trading volume, and turnover rate test with considering the intercept term. And all of the variables were tested without considering the trend. Based on the results, it is able to estimate the speed at which fast a deviation from equilibrium is adjusted back to the equilibrium level.

Table 11: Augmented Dickey-Fuller Test of the Variables

ADF(q)	Coefficient	Std. Error	t-Statistic	1% level	5% level	10% level	(C, T, K)
COVID19							
ADF (1)	-0.384776***	0.040399	-9.524381	-3.440387	-2.865860	-2.569128	(c, n,1)
Investor Sentiment							
ADF (1)	-0.477481***	0.039813	-11.993040	-3.440370	-2.865852	-2.569124	(c, n,1)
Market Index Return							
ADF (1)	-0.984834***	0.055901	-17.617570	-2.568592	-1.941320	-1.616366	(n, n,1)
Trading Volume							
ADF (1)	-0.119135***	0.021250	-5.606462	-3.440370	-2.865852	-2.569124	(c, n,1)
Turnover Rate							
ADF (1)	-0.115897***	0.020984	-5.523187	-3.440370	-2.865852	-2.569124	(c, n,1)
Volatility							
ADF (1)	-0.784233***	0.051651	-15.18333	-2.568597	-1.941321	-1.616365	(n, n,1)

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ Included observations: 640
where C stands for intercept term, T stands for trend term, K stands for lag order
Source: Author's calculations.

Table 12 displays that the half-life of the COVID19, investor sentiment, and market related variables is estimated through $\frac{\ln(0.5)}{\ln(1+\theta)}$ by using coefficients derived from a lagging Dickey-Fuller test(Akram, 2003), where the coefficient is obtained from a Augmented Dickey-Fuller with one lag. The half-lives of the variables are fast. The fastest one is the market index return. The adjustment speed of the COVID-19 is 1.43 days, and the investor sentiment is 1.07 days. Among the market-related variables, the longest time needed to adjust is the turnover rate of about 5.63 days; the adjustment speed of trading volume is 5.46 days; the speed of market index returns, and volatility is comparatively high; and the speed of volatility is 0.45 days. These estimates are narrowly ranging, show a significant short-term effect, and also indicate that short-term stock market fluctuations have been present during the COVID19 pandemic.

Table 12: Half-life Estimates Based on ADF Test

Variable	Half-life (days)	Prob.
COVID19	1.426907	0.0000***
Investor Sentiment	1.067869	0.0000***
Market Index Return	0.165480	0.0000***
Trading Volume	5.464267	0.0000***
Turnover Rate	5.627030	0.0000***
Volatility	0.451987	0.0000***

*Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ Included observations: 640*
Source: Author's calculations.

5. Conclusion

The half-life of the persistence of shocks in economic time series is defined as the time it takes for the impulse response of a unit shock to decay to half its initial value. This paper estimates the half-lives of investor sentiment, market index return, trading volume, turnover rate, and volatility under the COVID19 pandemic. During the research, the adjustment speed of the variable to the new equilibrium point is estimated, and the significant short-term association is proved as well. In this paper, two methods are respectively used to estimate the half-life, including based on AR model autocorrelation and ADF test coefficient estimates. Although the two methods present different results in terms of the value of the specific half-life, this may be due to the limitations of the estimation methods. However, they are in a narrow time range, which also reflects the fast adjustment speed and the significant short-term relationship among the variables.

In the analysis based on autocorrelation, we calculated the half-life of each variable by calculating the first-order autocorrelation coefficient of AR(p) under the condition that the AR (1) model is satisfied. In the model with COVID19 as the dependent variable, both the investor sentiment and the stock market-related index have short half-lives, which indicates that when these variables are affected by changes, they can adjust to the new equilibrium point within a short period of time. The half-life of investor sentiment is about 0.77 days, which indicates that investors could adjust to the market changes in a short period due to the sentimental impact of the COVID19 pandemic. The half-life on stock market-related variables, including the stock market index return, trading volume, turnover rate, and volatility, ranges from $0.78<h<0.80$ days; among them, the fastest rate of change is 0.78 days for the turnover rate, indicating that during the COVID19 pandemic, investors seemed to turnover in a short period to take advantage of stock market fluctuations to generate profits. From the half-lives of several other stock-market indexes, it also indicates that the stock market will fluctuate in a short period while adjusting to a new equilibrium point after receiving a shock from the COVID19 pandemic.

Secondly, when we study the half-lives of the impacts on each variable due to changes in investor sentiment. Based on the results of AR (1) model, we find that the half-lives of the COVID19 pandemic and stock market-related indexes are very short, ranging from 0.95 to 1.05 days. Under this criterion, the shortest half-life of stock market index returns is about 0.95 days. The fact that the half-lives of trading volume and turnover rate are relatively long, about 1.05, means that when investor sentiment is taken as the dependent variable, when each variable deviates from equilibrium, the adjustment speed is fast. In the meantime, it also shows that the impact of investor sentiment on other market-related variables under the COVID19 pandemic is short-term. Through the comparative analysis of the two groups of data that use different dependent variables, although the half-life of each response variable is relatively short when the COVID19 pandemic and investor sentiment are respectively used as the dependent variables. However, the half-life of the reaction to the shock caused by the COVID19 pandemic is comparatively smaller than the half-life of the reaction to the investor sentiment, which also shows that under the impact of the COVID19 pandemic, the investor sentiment and the stock market related index can reach equilibrium in a relatively short time that has a fast adjustment speed.

During the half-life estimation based on significant ADF test results, we use the correlation coefficient with the 1st lag order of ADF(p) to estimate the half-life of each variable after the shock. The results show that the half-life of each variable is relatively short and ranges from $0.17<h<5.63$ days, which shows that these variables can adjust to the new equilibrium point in a relatively short time after receiving a shock. Among them, the stock market index return shows a rapid adjustment speed with a half-life of 0.16 days, which indicates it can adjust to balance in a relatively short time after being impacted. In the second, the half-life of COVID19 is about 1.43 days, and the investor sentiment index is around 1.07days, which shows that investor sentiment can adjust quickly during the COVID19 pandemic. As mentioned earlier, the effective control measures may make the contributions. Among the stock market-related variables, it finds that the half-lives of trading volume and turnover rate are relatively high. Due to their mathematical correlation, their half-lives are closer, showing that the half-lives of trading volume and turnover rate are 5.46 days and 5.62 days, respectively. However, the overall half-lives are within a week, and it seems they have a fast adjustment speed. It is worth mentioning that the half-life of volatility is 0.45, which is a relatively fast adjustment speed, indicating that there probably will be fluctuations in the stock market in a short time when receiving a shock.

The above results show that the COVID19, investor sentiment, and stock market will return to the equilibrium point in a relatively short time when affected, which further shows that the external influence on each variable is short-term. During the COVID19 pandemic, there is short-term association between investor sentiment and the stock market. Meanwhile, the COVID19 pandemic can adjust in a relatively short period of time to the impact of investor sentiment, and it has possibly been questioned how the COVID19 pandemic, as a pandemic disease, can be affected by investor sentiment. As we mentioned in our literature review, investor sentiment affects behavior, which in turn affects decision-making, and as COVID19 is a pandemic spread from person to person, this is closely related to behavior. Additionally, why can investor sentiment adjust quickly to the impact of COVID19 in a short period? In fact, in China, the pandemic prevention and control measures are quite strict, such as social-distancing, quarantine, regional lockdown, and online learning, which effectively cut off most of the routes of transmission and also make the pandemic relatively stable in China. From the perspective of the data on half-life estimates of the variables, it seems to present a faster adjustment speed after shock due to the significant short-term association among them.

6. Practical Implications

In this paper, the half-life is estimated using different methods. The results show that the half-lives of all variables are estimated to be very short, around days, which also indicates that when COVID19, investor sentiment, and the stock market are affected, they can quickly adjust to the new equilibrium. Due to the persistence of the COVID19 pandemic, adjustments will be normal, and the fast adjustment speed of market related variables indicates that stock market fluctuations are very violent in the short term.

Investors who own stocks in companies with guaranteed performance should not overreact to short-term declines. According to the results of the half-life estimation, market movements caused by the pandemic tend to be short-lived, and the adjustment speed is fast. The market will soon show a rebound, and well-performing stocks will probably initially rebound. Therefore, investors who own those stocks are advised to stay confident. In addition, investors who have the underperforming stocks, themes, may take the opportunity of an adjustment to reallocate the positions for the shares and make a decision to buy the stocks of a guaranteed-performance company that is affected by the sudden events. Moreover, based on the fast adjustment speed, selling at a high price and buying at a low price can promote investors by creating high risk and high reward within a short period, but they should care about the risk.

Based on the half-life estimate results, it is suggested that the policymaker formulate short-term adjustment policies. As the data illustrate, COVID19 has a rapid adjustment speed, which cannot be achieved without effective pandemic prevention and control measures. If policymakers are advised to pick some measures to defend against COVID19, which are most likely to reduce the period needed to restore or maintain economic order to further ensure the sustainable development of the real economy, then the stock market will also be promoted. Additionally, due to investor sentiment, the stock market has a fast adjustment speed as well, which will make some enterprises unable to respond in a short time. It is suggested that corresponding financial security measures be provided to help them tide over the difficulties, which could be extended loan repayment, lower interests on loans, government procurement support, etc. Moreover, the speed of adjustment on investor sentiment is fast, and policy makers probably could take appropriate measures to manage information such as screening out untrue or exaggerated information from social media that can cause sentiment swings.

7. Limitations

This paper estimates the half-life of COVID19, investor sentiment, and the stock market. However, due to the influence of subjective and objective factors, this study still has limitations. In this paper, two methods are used to estimate the half-life. Since the estimation of the correlation coefficient may have the summation bias caused by the variance and the time aggregation bias caused by the random walk without drift caused by the minimum dummy variable estimation method, the specific results of the two methods are different. The data in this study are regional and time sensitive to some extent. As COVID19 research is still ongoing, the current research results can only be used as a reference for subsequent research, and there are certain limitations in the comprehensive interpretation of this problem. Each country or region has its own objective conditions, so the results of this paper are only used as a reference. The method of the article seems general, but the results may not be when switched to a different situation, possibly receiving different implications.

8. Future research

Future research in this field can continue to track the association among COVID19, investor sentiment, and the stock market, and test whether there is a long-term cointegration relationship among them. In addition, the article data can be extended to a global scope, which may help enrich the database and understand the global situation caused by the pandemic. Because the adjustment speed of all data in the results is fast, including the half-life of COVID19, which is specifically related to the exact pandemic prevention and control methods or not. It may provide a reference for later pandemic related policy design. With the development and research of COVID19 vaccine injection and pandemic, it seems interesting whether the association among COVID19, investor sentiment, and the stock market will change due to the addition of vaccine. We can even compare different results under different market backgrounds and different pandemic control methods and put forward targeted suggestions for investment in different markets.

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