The dynamic impact of COVID 19 on the US stock market

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Abstract. The outbreak of Corona Virus Disease in 2019 (COVID-19) has had a severe and long-lasting impact worldwide, with unprecedented disruptions to the US stock market in particular. This paper collects global and US data throughout the outbreak and develops empirical models, including a VAR model and an ARMA-GARCH model, to examine the dynamic impact of COVID-19 on the US stock market. According to the findings, COVID-19 will induce market volatility in the short term, as evidenced by shocks from new confirmed cases causing future shocks in returns that are decreasing in magnitude. In the long term, however, COVID-19 will not cause volatility in the US equity market. Therefore, depending on the stage, it is beneficial for investors to adopt appropriate strategies and the US government must develop effective policies.

Keywords: COVID 19, U.S, stock market, volatility.

1. Introduction

On March 11, 2020, the World Health Organization (WHO) officially declared COVID-19 a global pandemic, which has severely affected public health and survival due to its strong infectiousness and high lethality. As of February 24, 2022, the number of confirmed illnesses had surpassed 420 million, with around 5.9 million deaths (the COVID-19 data repository at the Johns Hopkins Center for Systems Science and Engineering). In addition, the worldwide outbreak of COVID-19 has greatly damaged the economic and financial situation, making it one of the most economically costly pandemics in recent history [1]. In particular, the COVID-19 disease led to unprecedented disruptions in the U.S. economy, as well as an unprecedented plunge in the U.S. stock market [2]. The ensuing financial crisis caused different stock market indices such as the S&P 500, Dow Jones Average, and NASDAQ to plummet until the government passed the Coronavirus Assistance, Relief, and Economic Security (CARES) Act on March 27, 2020, at which point the three indices rose by 7.3%, 7.73%, and 7.33%, respectively [3]. Furthermore, on April 9, 2020, the Federal Reserve Bank (Fed) unveiled a gigantic $2.3 trillion loan program that dwarfs past quantitative easing programs in scale and intensity (QE).

Since approximately two years into the outbreak, the policies that have been put in place to control the situation and in reaction to the recent changes in the US stock market, a slew of research examining the influence of COVID-19 on the market have sprung up. In 2020, Baker et al. report that COVID-19 has had an unprecedented impact on stock market volatility, and that government limitations on company activities and consumers enhance volatility. Onali discovers that confirmed instances of COVID-19 and deaths in numerous nations cause large increases in stock market volatility in the United States. However, volatility varies by industry; for example, higher-rated environmental and social companies have lower stock return volatility (Albuquerque et al.). In addition, Haroon and Rizvi investigate whether media coverage of COVID-19 is a volatility factor, and they find that changes in volatility have the greatest impact on the transportation, automotive, energy, and travel and leisure sectors, while most other sectors show no significant changes in volatility as a result of media coverage and news sentiment. Albulescu examines the impact of officially declared new COVID-19 cases and fatality rates on the volatility of US financial markets using ordinary least squares (OLS) regressions. He uses worldwide and US COVID-19 data to show that the epidemic increases the S&P 500's true volatility. He also contends that the long duration of the COVID-19 epidemic is a substantial source of financial volatility, creating a risk management challenge. William T Ziemba examines the plunge in the U.S. stock market during the epidemic and finds that indicators such as the 10-year Treasury bond, the S&P 500, Apple Computer stock, and the

enormous stimulus from the Federal Reserve and the government instead fueled the rebounding trend. Hee Soo Lee finds the COVID-19 sentiment on various sectors of the U.S. stock market's initial impact and further suggests considering a time lag perspective to visualize changes in correlation levels through time-lag differences for strategic investment planning. COVID-19 is the primary driver of significant developments in the US stock market in 2021, according to a study by Xue Gao, Yixin Ren, and Muhammad Umar published. If COVID-19 cannot be adequately regulated, accommodating monetary policy may be used as a stopgap remedy to keep the market stable. Claudiu Tiberiu Albulescu found that health crises enhanced the real volatility of the S&P 500 and showed that the prolongation of the coronavirus pandemic was an important source of financial volatility that challenged risk management activities. Maretno Agus Harjoto, Fabrizio Rossi & John K.Paglia use the WHO announcement of March 11, 2020, and the Federal Reserve Bank announcement of April 9, 2020, as two events that represent shocks and stimuli. This study finds that compared to other developed countries and emerging markets, the U.S. stock market experienced positive abnormal returns from the Fed stimulus, and the positive abnormal returns from the stimulus were obtained by large U.S. firms rather than small firms. In 2022, the findings of Sun-Yong Choi suggest that the pandemic enhances the volatility spillover effect, which reveals the financial contagion effect on the U.S. stock market.

Although the research arguments in this area are already relatively abundant, this study spans a longer period, i.e., from the time of the outbreak until the conflict between Russia and Ukraine. Besides, this research continues and combines the various directions already studied to better understand the factors that influence volatility through various indicators, time intervals of volatility, etc., what measures the U.S. has taken in response to this, and what changes in the stock market. As a result, this article examines the dynamic influence of the COVID-19 outbreak on the stock market in the United States over time.

Moreover, this paper examines the dynamic impact by building empirical models including VAR models and ARMA-GARCH models. Firstly, in the research design section, reliable sources of data are first stated, followed by unit root tests as this is the basis for building the models, and then these models are constructed separately. Secondly, in the empirical results and analysis section, the results are analyzed and summarized after the data are brought into the model calculations. Then, in the discussion section, the overall study is further discussed, explaining the reasons for the findings and their future applicability. Finally, a comprehensive summary of the findings of the paper is presented.

2. Research Design

2.1 The source of the data

The dynamic influence of the COVID-19 outbreak on the US stock market is examined in this research. On the one hand, the global and US daily number of confirmed new infections are the main indicators of the COVID-19 epidemic, and all daily data related to the COVID-19 are obtained from the COVID-19 data repository at the Johns Hopkins Center for Systems Science and Engineering [4]. The data from this database are mainly from authoritative official sources such as the World Health Organization, the US CDC, and the European CDC. In addition, Our World in Data, a website created by Oxford University, published an article on 19 March stating that the data published by Johns Hopkins University is significantly higher compared to WHO and the European CDC [5]. Therefore, the COVID-19 data repository of Johns Hopkins University has obvious credibility. On the other hand, the DJI, S&P 500, and NASDAQ are important indicators for learning about the US stock market, and all of their daily data comes from Investing.com [6], which provides real-time quotes and news information on hundreds of thousands of financial investment products, including global stocks, as well as a wide range of investment tools. According to SimilarWeb and Alexa, Investing.com is the second largest financial website in the world, with over 50 million monthly users and over 500 million visitors. As such, it is a trusted media outlet and provides highly credible data. It is worth noting that the daily closing prices are the basic data we use and study in this study. Considering the

impact of the conflict between Russia and Ukraine, the daily data (global and US daily new confirmed cases, DJI, S&P 500, NASDAQ) studied in this thesis started on 22 January 2020, when the first COVID-19 outbreak is confirmed in the US and ends on 24 February 2022, when the war between Russia and Ukraine is in full swing. To ensure the accuracy of the data matching, we set the date as the main consideration and the presence of these data (global and US daily number of confirmed new cases, DJI, S&P 500, NASDAQ) is essential. If not, the corresponding dates are ignored and not studied.

2.2 The unit root test

To test whether the daily data on DJI, S&P 500, NASDAQ, DJI returns, S&P 500 returns, NASDAQ returns and the global and US number of new confirmations are stationary, this thesis performs a unit root test. Xia Nanxin [7] suggests that the presence of a unit root in the time series should be determined before testing for a time trend and that only after rejecting the unit root hypothesis can a steady process with a trend be further investigated. Table 1 shows all the results for all daily data being tested.

Table 1. ADF-test

Variables	t-value	p-value
Stock index		
DJI	-1.693	0.7541
S&P 500	-3.358	0.0572*
NASDAQ	-0.843	0.9618
Rate of return		
DJI	-13.441	0.0000***
S&P 500	-15.251	0.0000***
NASDAQ	-15.815	0.0000***
COVID-19 pandemic		
Ln newly confirmed cases, USA	-5.606	0.0000***
Ln newly confirmed cases, Global	-7.676	0.0000***

Note: (i) ***, **, and * denote statistically significant levels of 1%, 5%, and 10%, respectively. (ii) DJI return = ln(p,t)- ln(p, t-1); S&P 500 return = ln(p,t)- ln(p,t-1); NASDAQ return = ln(p,t)- ln(p,t-1); Ln newly confirmed cases, USA = ln(p,t); Ln newly confirmed cases, Global = ln(p,t)

From Table 1, it can be seen that the test statistics for DJI, S&P 500, and NASDAQ are all greater than the 1% threshold. Therefore, we can accept the null hypothesis and obtain the result that DJI, S&P 500, and NASDAQ are not stationary. However, the p-values for DJI returns, S&P 500 returns, NASDAQ returns and the global and US number of new confirmations are all less than 1% and approximate 0.0000. Thus, we can reject the null hypothesis and obtain the results that DJI returns, S&P 500 returns, NASDAQ returns and the global and US number of new confirmations are stationary. Because examination of these data is a guarantee of further research, we only use DJI returns, S&P 500 returns, NASDAQ returns, and the global and US number of new confirmations as indicators for our study.

2.3 VAR model specification

Autoregressive (AR) models forecast by using the autocorrelation laws of the time series, i.e. they use information from the past to forecast the future. However, if one is concerned with forecasting several economic variables at the same time, the model can only forecast each variable separately using univariate time series. However, the vector autoregressive (VAR) model is a better solution, as it treats several variables as a system to make forecasts self-consistent.
The VAR model is shown below:

$$Y_t = \Phi_0 + \sum_{i=1}^{p} \Phi_i Y_{t-i} + \epsilon_t, \quad t = 1, 2, \ldots, T, \tag{1}$$

Where Y_t denotes the k-dimensional column vector of endogenous variables y_{it} ; $Y_{t?i}, i = 1, 2, \ldots, p$ is the lagged endogenous variable; p is the lag order; T is the number of samples; Φ_I is the k * k dimensional matrix of coefficients $?_{it}$ to be estimated and $?_t$ is the column vector of k-dimensional white noise ε_{it} , which can be contemporaneously correlated with each other, but not with their own lagged terms.

2.4 ARMA-GARCH model specification

Moving average models (MA) are used to predict the future using shocks from the past, which are combined with AR models to form ARMA models. In financial analysis, ARMA models are used to forecast the future using historical data and error terms. ARMA models are shown below:

$$y_t = \phi_0 + \sum_{i=1}^{p} \phi_i y_{t-i} + \varepsilon_t + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i}, \tag{2}$$

Where q is the order of volatility.

Both autoregressive conditional heteroskedasticity (ARCH) models and generalized autoregressive conditional heteroskedasticity (GARCH) models are used to analyze the volatility of financial factors. However, the GARCH model is more accurate than the ARCH model as it is an extension of the ARCH model and solves the problems caused by traditional econometrics of constant variance in time series variables. the GARCH equation in the ARMA-GARCH model is shown below:

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \sum_{i=1}^{q} \beta_i \sigma_{t-i}^2. \tag{3}$$

By adding the ARMA model to the GARCH model, we can forecast both returns and volatilities. In our project, we use the DJI, S&P 500, and NASDAQ as exogenous variables in the ARMA-GARCH model.

3. Empirical Results And Analysis

3.1 Impulse response

Before building the VAR model, the selection of the lag order of the model needs to be carried out. In this paper, we adopt the information criterion to determine the order, and its criteria for lag order selection include Final Prediction Error (FPE), Schwarz's Bayesian Information Criterion (SBIC), and Hannan and Quinn Information Criterion (HQIC). According to table 2, there are two information criterion metrics that both indicate the use of 12th order lags, so we used 12th order as our lag order.

Table 2. VAR model identification

Lag	FPE	AIC	HQIC	SBIC
1	1.8e-17	-24.3872	-24.2894	-24.1377
2	5.3e-18	-25.5916	-25.4123	-25.1343
3	3.9e-18	-25.8963	-25.6355	-25.2311*
4	3.8e-18	-25.929	-25.5867	-25.0559
5	2.9e-18	-26.1768	-25.7529	-25.0958
6	2.4e-18	-26.362	-25.8566	-25.0731

7	2.2e-18	-26.4677	-25.8809	-24.971
8	1.9e-18	-26.6025	-25.9342	-24.8979
9	1.6e-18	-26.8197	-26.0699	-24.9072
10	1.3e-18	-27.017	-26.1856	-24.8966
11	8.7e-19	-27.4063	-26.4934*	-25.0781
12	8.1e-19*	-27.4787*	-26.4843	-24.9425

Note: * denotes the minimum value under this information criterion, i.e. the optimum order

With the variables and lag orders in place, this paper is ready to proceed with the modeling. However, as the equations of the VAR model are not the main purpose of our project, the results are not shown.

After estimating the VAR model, it is necessary to test whether the VAR system is a stationary process. If all the eigenvalues are inside the unit circle, then it is a stationary process. A plot of the relationship between the eigen roots of the companion matrix and the position of the unit circle is shown in figure 1.

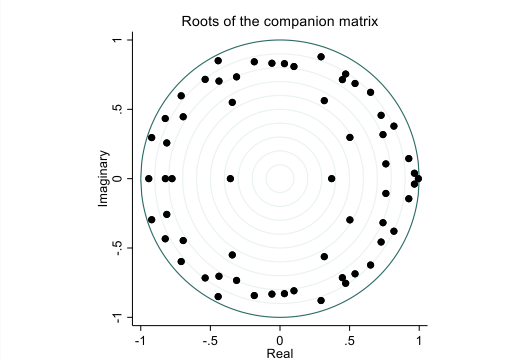

Figure 1 The unit circle of the VAR model

The results above show that all the eigenvalues are inside the unit circle and are therefore a smooth process.

The impulse response function (IRF) captures the dynamic impact of a one-unit shock on the other variables in the VAR model and is shown in the formula below:

$$\frac{\partial y_{t+s}}{\partial \varepsilon_t} = \psi_s \,, \tag{4}$$

It represents the effect on the value $y_{i,t+s}$ taken by the i-th variable in period (t+s) when the j-th variable's perturbation term ε_{jt} in period t is increased by one unit (while all other variables remain unchanged from the other periods).

The impulse response graph drawn from the dynamics of these variables over the period following this shock is shown in figure 2.

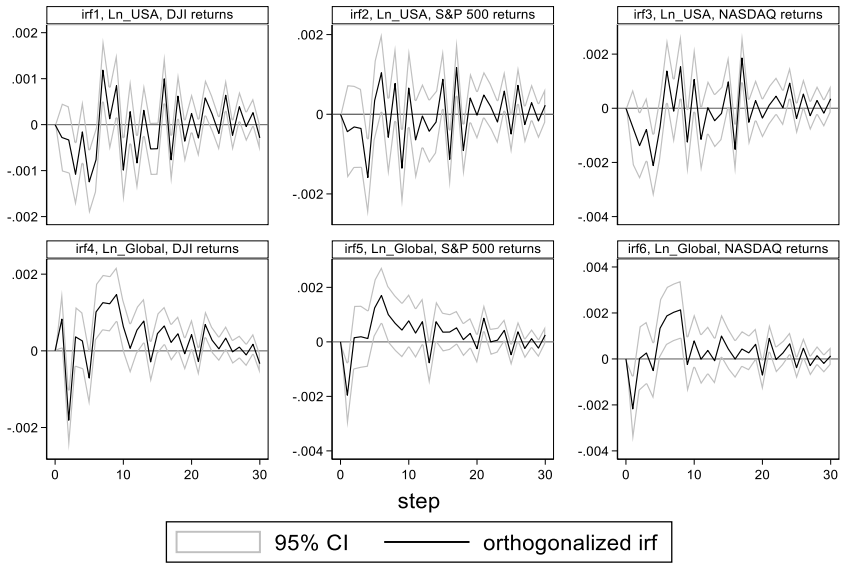

Figure 2 Impulse response diagrams

Note: Graphs by irfname, impulse variable, and response variable

Each row in the impulse response graph shows the effect of the same shock on a different variable and each column shows the effect of a different shock on the same variable. The horizontal coordinates are scaled in units of time as estimated by the VAR model (in this case one day) and the vertical coordinates are measured in each response variable's units. Thus, the graphs above show the impact of a unit shock to an impulse variable on other response variables over a 30 period.

The first row shows the impact of the global logarithm of the number of new daily confirmed cases on the VAR system: DJI returns, S&P 500 returns and NASDAQ returns are subjected to the shock in a similar overall trend, i.e. they fluctuate sharply in the first 20 periods and then the impact slowly declines. DJI returns reach their lowest value in period 5 and peak in period 7; S&P 500 and NASDAQ returns reach their lowest value in period 4 and peak in period 17.

The second row shows the impact of the logarithm of the number of new daily confirmed cases in the US on the VAR system: DJI returns, S&P 500 returns and NASDAQ returns are subject to a similar overall trend, i.e. they fluctuate sharply in the first 10 periods and then the impact slowly declines. DJI returns reached their lowest point in the period 2 and peaked in period 9; S&P 500 returns were lowest in the period 1 and highest in period 6; Period 1 saw the lowest NASDAQ returns and period 9 saw the highest.

In the short term, therefore, the COVID-19 epidemic has caused volatility in the market, as evidenced by the fact that shocks from new confirmed cases can cause returns to oscillate in the future, and a notable feature is that the magnitude of the oscillation is decreasing.

3.2 Determining the order of the mean value equation

In this case, to investigate the influence of the COVID-19 epidemic on the indices of DJI returns, S&P 500 returns and NASDAQ returns, their mean equations, i.e. the ARMA component of the respective ARMA-GARCH models, are constructed separately. Before constructing the respective mean equations, we use DJI returns, S&P 500 returns and NASDAQ returns as the independent variables of the respective models and choose PACF and ACF to confirm the orders of AR () and MA () in the ARMA models respectively. The following are the results of the PACF and ACF data for DJI returns, S&P 500 returns and NASDAQ returns respectively.

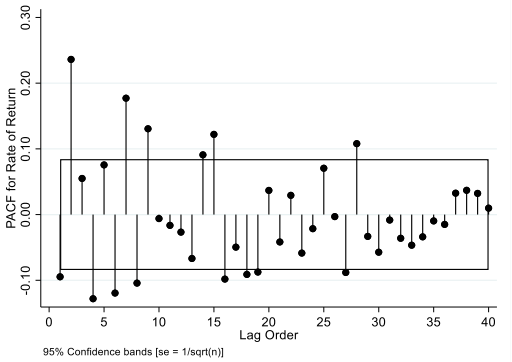

Figure 3 PACF test of AR model for DJI returns

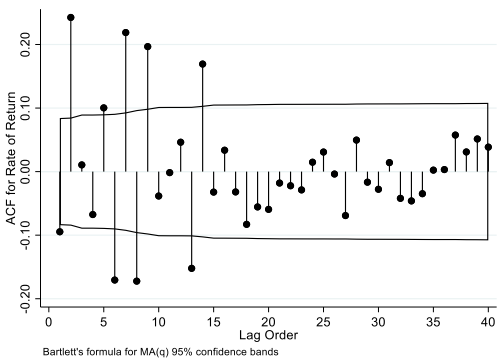

Figure 4 ACF test of MA model for DJI returns

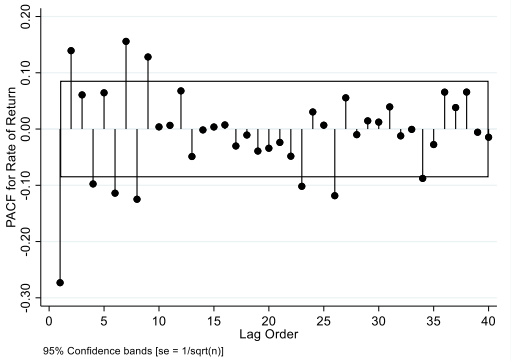

Figure 5 PACF test of AR model for S&P 500 returns

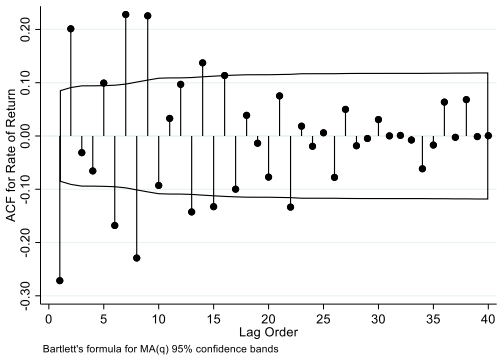

Figure 6 ACF test of MA model for S&P 500 returns

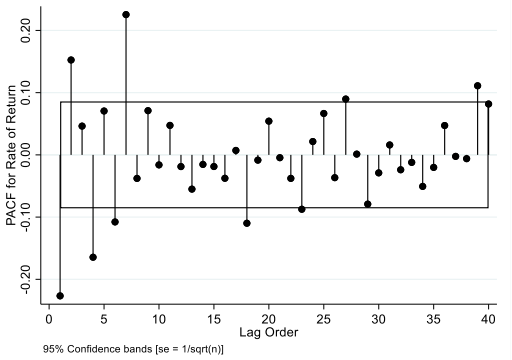

Figure 7 PACF test of AR model for NASDAQ returns

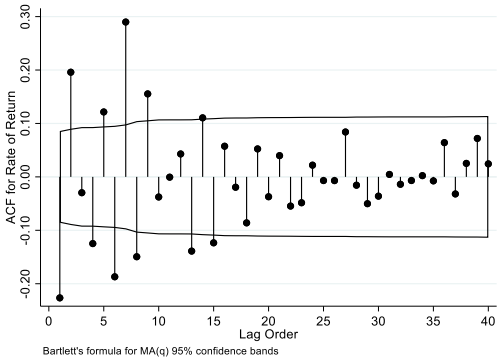

Figure **8** ACF test of MA model for NASDAQ returns

Based on the PACF and ACF tests shown above (figure 3, figure 4, figure 5, figure 6, figure 7, and figure 8), and by adjusting the orders so that the model passes the test that the residuals are white noise, the results are that the orders of the mean equation for DJI returns are AR(2 4 6 7 8 9 13 14) and MA(2 6 7 8 9 13 14); the orders of the mean equation for S&P 500 returns are AR(1 2 4 6 7) and MA(1 2 4 5 6 7). The order of the mean equation for NASDAQ returns is AR (1 2 4 7 8) and MA (1 2 7 8 9).

3.3 Results of ARMA-GARCH model and conclusions

The results in Table 3 were obtained by adding the mean equation for DJI returns, S&P 500 returns and NASDAQ returns to the variance equation

Table 3. ARMA-GARCH model, Variance equation

	(1)	(2)	(3)
Rate of return, DJI			
Ln newly confirmed cases, USA	-0.1654***		-0.1465
	(0.0262)		(0.09617)
Ln newly confirmed cases, global		-0.2666***	-0.0335
		(0.0450)	(0.1754)
ARCH (-1)	0.1286***	0.1555***	0.1309***
	(0.0317)	(0.0355)	(0.3256)
GARCH (-1)	0.7981***	0.7641***	0.7941***
	(0.0434)	(0.0512)	(0.0481)
Constant	-9.5491***	-7.3607***	-9.2358***
	(0.4947)	(0.8588)	(1.8163)
Rate of return, S&P 500			
Ln newly confirmed cases, USA	-0.0806**		0.2038
	(0.0384)		(0.1166)
Ln newly confirmed cases, global		-0.1879***	-0.4947*
		(0.0693)	(0.2096)
ARCH (-1)	0.2383***	0.2371***	0.2820***
	(0.0621)	(0.0652)	(0.0771629)
GARCH (-1)	0.6871***	0.6631***	0.5934***
	(0.0721)	(0.0826)	(0.0989)
Constant	-9.4843***	-7.2933***	-4.920***
	(0.6767)	(1.2894)	(2.0755)
Rate of return, NASDAQ			
Ln newly confirmed cases, USA	-0.1499***		0.0008
	(0.0351)		(0.0967)
Ln newly confirmed cases, global		-0.2552***	-0.2509
		(0.0625)	(0.1644)
ARCH (-1)	0.1359***	0.1520***	0.1607***
	(0.0383)	(0.0408)	(0.0448)
GARCH (-1)	0.8094***	0.7937***	0.7787***
	(0.0448)	(0.0480)	(0.0520)
Constant	-9.0824***	-6.9718***	-6.9278***
	(0.5968)	(1.0561)	(1.4839)

Note: ***, ** and * represent significant at the 1%, 5% and 10% levels of significance respectively

According to table 3, in terms of magnitude and significance, the difference in the global number of new daily confirmations has a more significant impact on DJI earnings, S&P 500 earnings, and NASDAQ earnings than the difference in the number of new daily confirmations in the US. However, the global and US logarithms of new daily confirmed cases have similar effects on DJI returns, S&P 500 returns and NASDAQ returns. In terms of the variance equation, in the long run, the coefficient on the number of new US and global confirmations is negative, indicating that the new coronary pneumonia outbreak did not cause volatility in the US equity market.

In this case, based on all of the above results, the long-term impact on the US equity market in the context of the COVID-19 pandemic is minimal, although the number of new global confirmations has a greater impact on the US equity market compared to the number of new US confirmations.

4. Discussion

The above contributions suggest that in the short term, the COVID-19 outbreak can indeed cause dramatic volatility in the US stock market as a whole, with stock market indicators trending lower and then higher, before slowly becoming less volatile. In particular, the daily number of new confirmations in the US causes greater volatility and lasts longer than globally. This may be since the outbreak situation in the US is more of a local concern and the public panic due to news reports, which in turn leads to increased volatility in the US stock market [8]. At the same time, government restrictions on business activity and consumers in the process of controlling the epidemic can also increase volatility [1]. However, the massive stimulus measures [9] and accommodative monetary policy [10] of the Federal Reserve and the government may have contributed to the rebounding trend in the stock market. As a result, the unpredictable short-term movements of the COVID-19 epidemic could have a significant influence on the US equity market.

The influence of the COVID-19 outbreak on the US equities market is minimal in the long run, and it does not generate market volatility. This may be because the outbreak has been effectively

contained. As a result, the number of new daily confirmed cases globally and in the US has decreased, news coverage has become progressively more positive and government policies have played a role. As a result, COVID-19 is no longer a major factor affecting the US stock market.

It can therefore be concluded that in the short term, the COVID-19 epidemic will undoubtedly affect the US equity market. This impact includes the direction of change in equity yields and the degree of volatility in equity yields. The US government should properly guide public sentiment, enhance control of the epidemic and adopt effective and feasible policies in light of the current state of the epidemic. As a result, the trend of lower US equity markets is mitigated and volatility is reduced. In addition, the volatility of the US stock market can be kept within a certain range if the future trend of the COVID-19 outbreak can be accurately predicted. This also makes it possible for the US government to anticipate its market crises and take hedging measures accordingly. In addition, while the number of new confirmed cases in the US is more likely to cause volatility in the story compared to the global one, the global number of confirmed cases has a non-negligible impact on the stock market, so it is necessary for countries to work together to combat the global health crisis.

In the long run, there is no need to be concerned about the epidemic's influence on the US share market, while the epidemic needs to be well controlled to prevent a recurrence. If a similar event occurs in the future, the government can use this experience to study the factors affecting the stock market and develop a plan to stabilize or even stimulate the rise of the stock market.

5. Conclusion

This paper focuses on the dynamic impact of COVID-19 on the US stock market. The results of the applied VAR model demonstrate that the US share market is inextricably tied to the COVID-19 outbreak, with COVID-19 triggering dramatic changes in the US stock market in the short term but eventually diminishing the severity of the shocks. In particular, the number of new confirmed cases in the US has a greater impact on the US stock market than globally. Therefore, it would be a better option for the US government to give more consideration to and implement local measures. In addition, proper forecasting of the trend of the epidemic and timely arrangement of response strategies could lead to a stable or even rising stock market. However, the results of applying the ARMA-GARCH model show that the COVID-19 epidemic does not have an impact on the US stock market in the long run. Therefore, one need not worry unduly and the government needs to manage the epidemic well in the long run to prevent another outbreak.

For those who are concerned about the influence of the COVID-19 pandemic on the US equities market and want to make the proper measures, take a look at this article. This article is simply a case study describing the impact of the COVID-19 epidemic on the US stock market in the short and long period. Investors can adjust their investment strategies appropriately in light of the epidemic and future trends in the stock market. In addition, the government can use the indicators of the COVID-19 as a reference to appropriately predict the development of the stock market and take timely preventive measures to maintain the balance of the stock market.

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