

# The Impact of Covid-19 on the US Stock Market: Evidence from Time Series Model

Tian Qiu

Department of Finance, University of British Columbia, Vancouver, Canada

tqiu02@ubc.student.ca

**Abstract.** In this study, we conduct a time series analysis of the US stock market's response to the COVID-19 pandemic. Using both US and global daily COVID-19 newly confirmed cases and stock market returns data represented by Nasdaq, S&P 500, and Dow Jones over the period 31 December 2019 to 30 December 2021, we examine a time-series impact of COVID-19 on the US stock market. We employ our input into a vector autoregression model (VAR) and ARMA-GARCH model to characterize the dynamic relationship between both domestic and global COVID-19 infections and the performance of the US stock market. The findings show that COVID-19 has an initial negative shock on the stock market with large volatility clustering within 60 days after the initial pandemic outbreak. After around 200 to 300 days, the number of new COVID-19 cases per day does not have a statistically significant impact on the US stock market.

**Keywords:** COVID-19; US Stock Market; VAR Model; ARMA-GARCH Model; Time Series Analysis.

## 1. Introduction

On March 11, 2020, COVID-19 virus outbreak has officially been declared as a global pandemic by the World Health Organization (WHO). Since the first cases were reported to the WHO in December 2019, COVID-19 cases have been totaled to around 508.2 million and have caused 6.2 million deaths by April 2022 [1]. Among the 223 countries and territories infected, the United States has the most confirmed cases. The long-lasting and massive shock wreaks a brutal impact on the global economy, triggering one of the deepest recessions in history which saw an estimated global growth contraction of 3.5% [2]. In the short term, as many countries adopt lock-down and quarantine policies, social and economic activities are significantly constricted. In the long-term, consequences of the pandemic may be by-products of global recession such as mass unemployment, business failures, and a severely stagnated global economy.

While the exact global economic impacts are yet unknown, financial markets have quickly reacted with a global stock market. Within three months after the initial COVID-19 outbreak, the equity crash of 30% loss to market capitalization even exceeded the crash in the 2009 global financial crisis [3]. Stock markets in the US, Europe, and Asia have all tumbled by more than 10%, marking their largest one-day drop since Black Monday of 1987. Especially for the US stock markets, in March, it hit the circuit breaker mechanism four times in ten days. This circuit breaker has been only triggered once in 1997 since its inception in 1987. In March 2020, the free fall of 29.6% YTD in Dow Jones has also marked its worst yearly performance since the financial crisis of 2008 [4].

Several studies have already thoroughly examined the initial impact of the pandemic on financial markets. For instance, a study done by Ashraf in 2020 showed that in the period of the initial COVID-19 outbreak from January 2020 to April 2020, global stock markets reacted strongly with negative returns to growth in confirmed cases, whereas reaction to the growth in deaths rate was not statistically significant [5]. Economic implications were carefully studied as well to justify the dramatic movements in stock markets. According to Youssef et al., stock markets were impacted by the COVID-19 pandemic through two channels [6]. On the macroeconomic level, high-level economic policy uncertainty stemming from the virus's infection pattern and the unpredictable future situation regarding the pandemic led to volatile and low cash flow expectations, resulting in stock market depreciation. The other more direct impact was related to the immediate halting of industrial, tourism, aviation, and other sectors, directly affecting the stock index by depreciating relevant stocks [6].

However, while most of the existing studies emphasize analyzing the initial stage of the COVID-19 pandemic on stock markets in 2020, few have yet to extend studies to observe impacts after 2020, when stimulus packages, fiscal policies, vaccination controls, and other responsive measures were widely in place to restore market order. For instance, the US stock market, although initially, experienced several record-breaking plunges in its stock market history in early 2020, the stock market represented S&P 500 surged almost 65% from the March low by the end of 2020. The stock market continued to climb higher in 2021, with the S & P 500 index hitting a series of all-time closing highs [7].

While the US stock market is steadily rebounding to the pre-pandemic level thanks to monetary and fiscal policies imposed by the Federal Reserve (FED), the newly confirmed cases in the US are still experiencing waves of dynamic fluctuation. How significant is the role of COVID-19 in the stock market performance? Is it safe to say that COVID-19 may no longer pose a threat to the stock market with the responsive measures in place? In this paper, our main objective is to explore the time series impact of the COVID-19 pandemic on the US stock market using VAR and ARMA-GARCH models. Although COVID-19 is still in its spreading phase, using data ranging from 31 December 2019 to 30 December 2021 can extend the previous study on the initial shock of the stock market to include the relatively longer-term impact of the pandemic. Daily stock market returns data from three major US market indices, S&P 500, Dows Jones, and Nasdaq will be used to examine the impact of growth in global and domestic COVID-19 daily confirmed cases after controlling for systematic risk.

The rest of the paper proceeds as follows: Section 2 outlines our research construction procedures including data source, empirical methodologies, and model specifications. Section 3 presents the empirical results and brief analysis. Section 4 reports a discussion based on existing literature. The final section concludes the study.

## **2. Research design**

### **2.1 Data**

In this study, we examined the time-series impact of COVID-19 on the US stock market over the period from 31 December 2019, the beginning of COVID-19, to 30 December 2021, one month before the Russian invasion of Ukraine. The time frame was chosen to fully capture the time-varying impact of the ongoing pandemic to avoid significant impacts from external lurking variables such as the Russian-Ukraine crisis. To quantitatively reflect the severity of the pandemic, we employed both the US and global daily new confirmed cases. Case numbers were derived from the World Health Organization (WHO) through official communications under the International Health Regulations as well as monitoring of the official ministries of health social media platforms. Although under or overestimation of true cases might exist due to varying local adaptations, testing strategies, reporting practices, and lag time, the data from 31 December 2019 to the 30 December 2021 were mostly reliable since significant data error has already been corrected by WHO at a frequent interval [8].

Financial data in this paper were based on the real-time recording of the US stock market, which was represented by three major market indices including Nasdaq, Dow Jones, and S&P 500. These three major market indices were chosen to include a wider range of sectors, companies, and stock types that can provide a more accurate gauge of the US stock market's performance.

### **2.2 Augmented Dickey-Fuller (ADF) test**

According to Pickup, a major assumption of time series analysis is to have stationarity, a requirement for certain properties in time-series data (i.e., mean) to remain stable over time [9]. If a time series model is nonstationary in nature, a random walk exists as there is no predictive relationship between independent and dependent variables. Stationarity can be tested by conducting a unit root test. Therefore, before we proceed to develop time series models, we first test for the presence of a unit root through an augmented Dickey-Fuller (ADF) test denoted by a fitting regression as below:

$$x_t = c_t + \beta x_{t-1} + \sum_{i=1}^{p-1} \phi_t \Delta x_{t-i} + e_t \tag{1}$$

The test hypothesis is:  $H_0: x_t$  is a random walk around a trend or  $\beta = 0$  , and  $H_1: x_t$  is trend stationary process or  $\beta \neq 0$ .

Three major categories of variables are tested using STATA with a lag number of 1, including raw index, rate of return, and COVID-10 pandemic cases (see Table 1).

Based on ADF test results show. In table 1, the p-value of the raw index is significantly greater than the significance level of 0.05. Therefore, the null hypothesis is rejected, and raw indices do not qualify for stationarity. This phenomenon is representative of actual market performance as the past period index cannot accurately predict future performance. Dramatic fluctuations in stock price exist as sudden external forces, such as the unexpected hit of COVID-19, fall upon the market. On the other hand, the rate of returns is more suitable data for time series analysis as their p-value is 0, indicating an absence of unit root and a stationary series.

For US daily new confirmed cases, they are stationary as the p-value is significantly less than 0.05. For global cases, however, the data is not stationary using a 0.05 significance level but can be stationary if using a 0.1 significance level. The minor controversy in the data’s stationarity might be caused by certain data errors from collecting and processing massive, global data. In this research, we consider global daily new confirmed cases to be stationary.

**Table 1. ADF-test**

Variables	t-statistic	p-value
	Raw index	
NASDAQ	-2.118	0.5360
S&P 500	-2.898	0.1630
Dow Jones	-2.868	0.1729
	Rate of return	
NASDAQ	-15.721	0.0000***
S&P 500	-15.367	0.0000***
Dow Jones	-14.734	0.0000***
	COVID-19 pandemic	
The US	-4.858	0.0004***
Global	-3.374	0.0549*

Note: the raw index has the unit root and is a random walk around a trend while the rate of return and pandemic cases are stationary.

### 2.3 VAR model specification

In this research, a five-variable vector autoregression (VAR) model is used to empirically investigate the impact of COVID-19 daily new confirmed cases on US stock market performance. According to Song and Bickel, the VAR approach can model high-dimensional time series in one step, as well as it allows for impulse response analysis which is easy to interpret [10]. Thus, we will use the VAR approach for simplicity and clarity of time series analysis.

The general model specification of a VAR model is expressed as follows:

$$Y_t = \Phi_0 + \Phi_1 Y_{t-1} + \dots + \Phi_p Y_{t-p} + BX_{t+\epsilon t}, t = 1, 2, \dots, T \tag{2}$$

Where  $Y_t = (Y_t, 1, \dots, Y_t, m)$  is a  $1 \times k$  vector of the dependent stationary variables, which includes the performance (or daily returns) of the US stock market represented by NASDAQ, Dow Jones, and S&P500 at time t, and a set of regressors which include the US and global daily new confirmed cases.  $X_t$  is a  $1 \times I$  vector of exogenous variable, which includes the new confirmed cases per day of COVID in both US and global realm; and B is a matrix of  $I \times k$  of parameters.  $\epsilon t$  is a sequence of serially uncorrelated random vectors. p is the number of lags and T is the number of time series. To provide better economic inferences, log returns and log counts of all the variables will be used in this study, which can be calculated based on the formula below:

$$r_t = \ln P_t - \ln P(t - 1) \tag{3}$$

**2.4 ARMA-GARCH model specification**

In this paper, the effectiveness of autoregressive moving average (ARMA) models with various generalized autoregressive conditional heteroskedasticity (GARCH) approaches, also called the ARMA-GARCH model, is used to assess the time-series impact of COVID-19 on the US stock market. The main advantage of the ARMA-GARCH model is that it combines an ARMA model for including the strong correlations between adjacent measurements, which can improve model precision, and a GARCH model for extracting the nonlinear characteristic that exhibits volatility clustering [11]. In total, six ARMA-GARCH models were built to analyze the impact of either domestic or global daily new cases on each of the three major indices.

The general specification of ARMA-GARCH model includes the following terms:

$$y_t = C + \sum_{i=1}^m \phi_i y_{t-i} + \sum_{j=1}^n \theta_j \varepsilon_{t-j} + e_t \tag{4}$$

$$\sigma_t^2 = \eta + \sum_{i=1}^p \beta_i \sigma_{t-1}^2 + \sum_{j=1}^q \alpha_j \varepsilon_{t-j}^2 \tag{5}$$

Wherein equation (4),  $y_t$  is log form of market index daily return, C is a constant term,  $\phi_i$  are the parameters of the autoregressive component of lag m,  $\theta_j$  are the parameters of the moving average component of lag n, and  $\varepsilon_t$  is the error term at time t. The selection process for lag order m and n will be explained in section 3.1. In notation (5),  $\eta$  is the long-run volatility,  $\beta_i$  and  $\alpha_j$  are constant coefficients, p and 1 are lag orders. In this paper, another term representing the exogenous variables of either US daily new confirmed cases or world daily new confirmed cases is also included in the ARMA-GARCH model to explain the impact of COVID-19 on the US stock market performance.

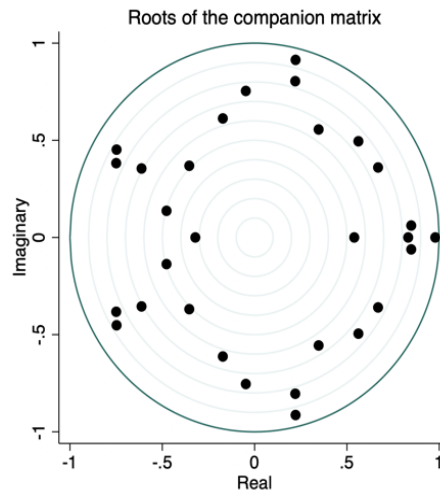
**3. Empirical results and analysis**

**3.1 VAR model lag order selection**

A study done by Liew in 2004 found that the Hannan-Quinn information (HQIC) criterion is most suitable for correctly estimating the true lag length for a large sample size with over 120 observations [12]. Since our data size is 505, we use the HQC criterion to determine the optimal autoregressive lag selection. After executing varsoc function via STATA, the HQC criterion suggested six lags (see Table 2). Each VAR model passed the stability check as all the eigenvalues are inside the unit circle shown in Figure 1.

**Table 2.** Lag Selection from SATA

Lag	HQIC
0	-15.0634
1	-21.5225
2	-21.5027
3	-21.5633
4	-21.6126
5	-21.5214
6	-21.9527*
7	-21.9027
8	-21.7901
9	-21.7334
10	-21.7334
11	-21.5052
12	-21.4508



**Fig. 1** VAR stability check

### 3.2 Impulse response

Impulse response functions are computed based on the Choleski decomposition, which generated six results visualized in Figure 2. Figure 2 shows the dynamic effect of daily registered cases of COVID-19 pandemic on daily returns of the US stock market represented by Nasdaq, S&P 500, and Dow Jones. The impulse response functions are obtained from the VAR model established in section 2.3 with six lags. The graphs in the left-hand column show the impulse response function of US domestic daily registered infection cases; the graphs in the right-hand column show the impulse response function of global daily registered infection cases. 30 steps are used to visualize the impulse response over 505 trading days from 31 December 2019 to 30 December 202. Thus, each step represents approximately 17 trading days.

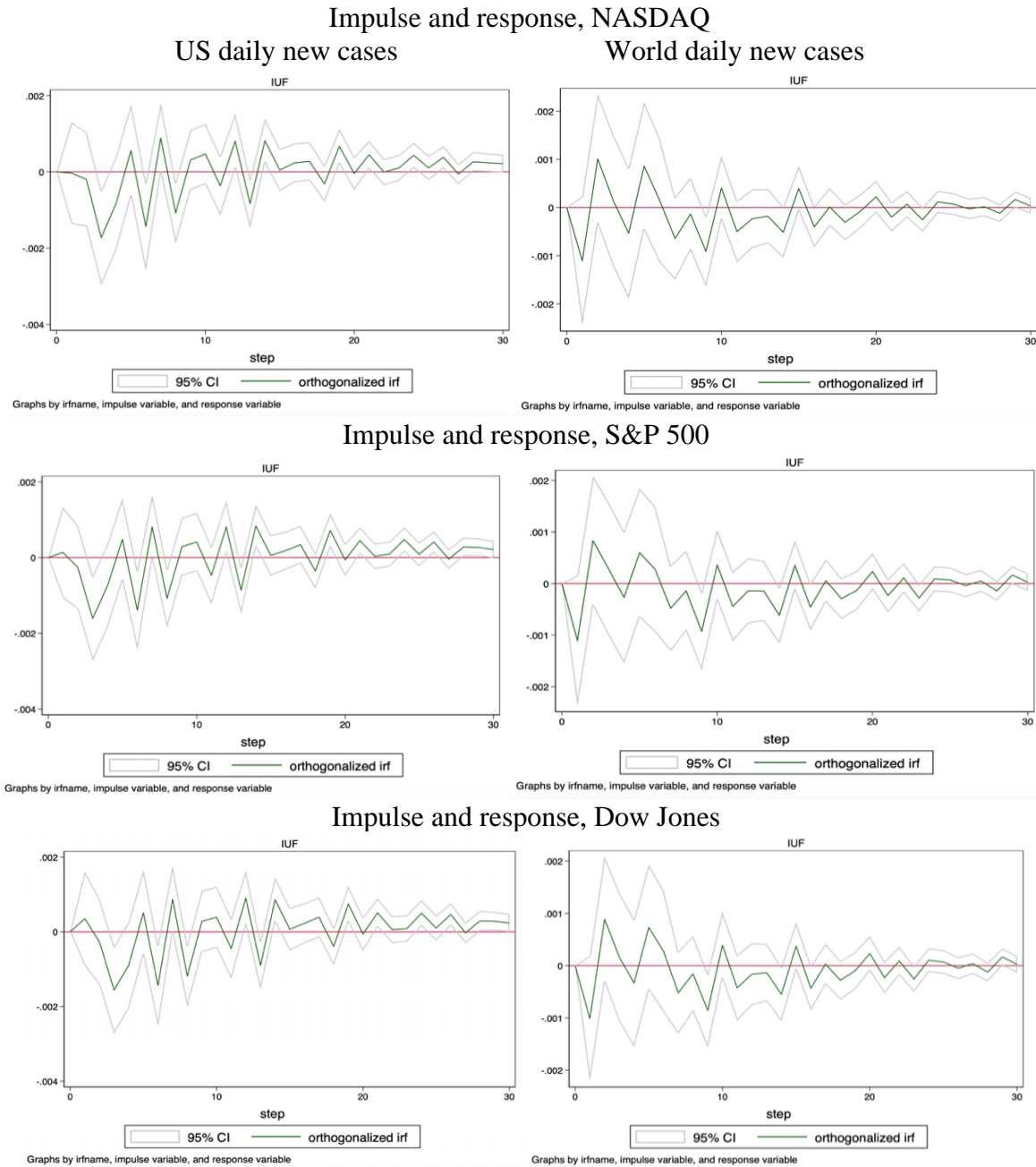
Impulse responses of all three indices share a very similar trend, in which relatively more dynamic fluctuations persist within 20 periods since the beginning of the pandemic, and then gradually die out to fluctuate around zero. The trend similarity displayed in the three indices showed that on a macroeconomic level, COVID-19 infections exert a comparable impact on companies of all sizes, sectors, and stock types (i.e., value stock, growth stock).

The left-hand figures of US impulse responses show waves of dynamic fluctuation, in which each time when there exists a negative peak, a positive peak will follow around two periods (or a month) later. The negative peak effects occur on step 3 (day 51), step 6 (day 102), step 9 (day 153) and step 13 (day 221), in which the most extreme negative peak effect takes place at step 3, around two months since the beginning of COVID-19. At peak, a one standard deviation increase in new cases of COVID-19 infections in the US decreases the daily return of Nasdaq, S&P 500, and Dow Jones by around 0.18 percentage points. The positive peak effects occur at approximately step 5 (day 85), step 7 (day 119), and step 12 (day 204), in which the largest positive peak effect at step 7 shows an increase in US stock market return by around 0.1 percentage point. Both positive and negative peak effects gradually die down to fluctuate around zero after period 13, which is about seven months since the beginning of COVID-19. Such decreasing trends in peak effect and dynamic fluctuation can be explained by mediating pandemic responses such as vaccines and fiscal policy.

According to the right-hand graphs, impulse responses of global daily new confirmed cases seem to be more responsive as compared to domestic COVID-19 infection. Substantial fluctuations occur at earlier steps where the most extreme negative peak takes place in step 1 followed by the largest positive peak effect in step 3. After waves of initial fluctuations, the effect gradually regresses around zero after step 10, which is around six months since the beginning of COVID-19.

In summary, the empirical findings from impulse responses show that the decline in the US stock return is the most pronounced during the initial period between 40 to 60 days after the domestic COVID-19 outbreak, which is consistent with a previous study done by Ashraf in 2020 [5]. However, a notable increase in stock return soon recovers the negative peak effect within 50 days following the

sharp decline in stock return, creating dynamic waves of fluctuation in US market performance. After around 200 to 300 days, the number of new cases no longer exert significant influence on US stock market performance as compared to the impact in the initial pandemic outbreak stage. Therefore, the number of domestic and global COVID-19 infections per day, which was previously assumed as a main driver of US stock market performance, does not have a statistically significant impact when a longer time frame of the pandemic outbreak is examined.



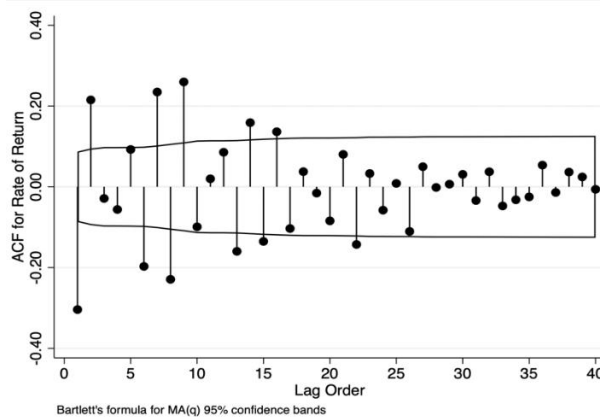
**Fig. 2** Impulse and response for three US market indices

### 3.3 ARMA model lag order selection

We use autocorrelation function (ACF) and partial autocorrelation function (PACF) plots to determine the order of AR and MA terms for the ARMA-GARCH model. After plotting ACF and PACF graphs for each of the five variables, a gradual decreasing pattern is shown in all plots, indicating that the ARMA process is appropriate for modeling.

Based on the ACF and PACF plots, we can manually identify significant lags for MA and AR respectively. For instance, as shown by the ACF plots of Nasdaq rate of return in Figure 3, significant

lags are found in lags 1, 2, 3, 4, 6, 7, and 9. For model simplicity later used for ARMA-GARCH, we will select lag 1, 2, 3, 4. After lag selection, we then conduct Portmanteau test for white noise to ensure the ARMA model's assumption of following a white noise process. If the p-value of the model with selected lags is greater than 0.05, we cannot reject the null hypothesis, implying that the variable tested is indeed a white noise process. Otherwise, the lag orders should be reselected and retested to meet the white noise assumption.



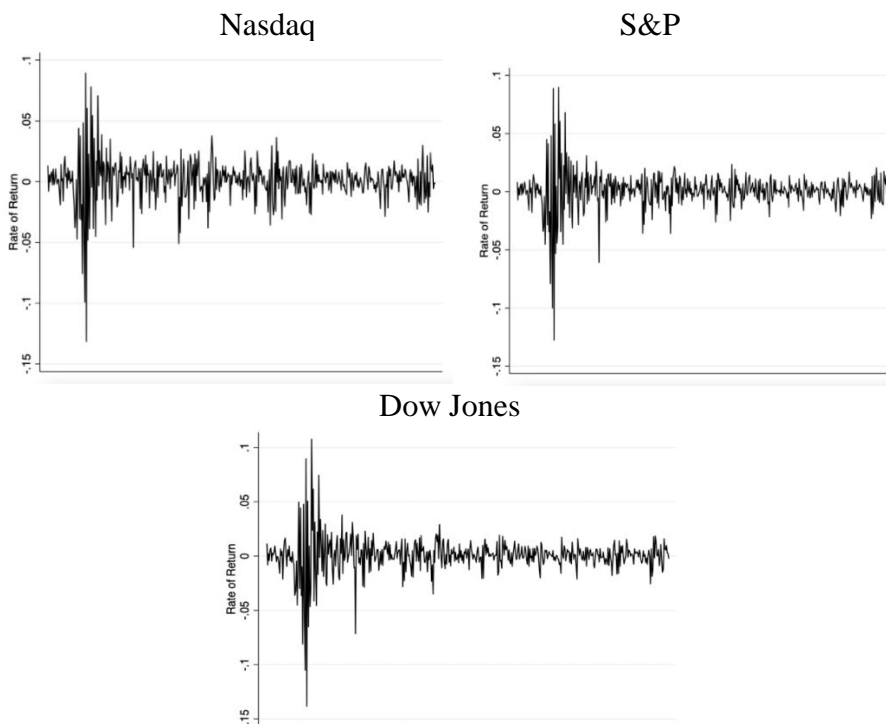
**Fig. 3** ACF plot, NASDAQ

Following the lag selection process explained above, we have derived lag orders for the rate of return series of Nasdaq, S&P 500, and Dow Jones as shown below in Table 3:

**Table 3.** ARMA order identification

Variables	AR	MA
NASDAQ	1, 2, 6, 7	1, 2, 6, 7
S&P	1, 2, 3, 4, 6	1, 2, 4, 5, 6
Dow Jones	1, 2, 3, 4	1, 2, 4, 5

**3.4 ARMA-GARCH estimated results**



**Fig. 4** Yield trend

Table 4 showcases all parameter estimates and their respective standard error from a total of six ARMA-GARCH models. As shown in Table 4, for each model, all coefficients of ARCH and GARCH error terms are statistically significant with a p-value greater than 0.05 and t-statistics greater than |2|. The significant coefficients of ARCH- and GARCH- terms indicate that the error terms are heteroskedastic and ARMA-GARCH model can be applied. The visualization of GARCH model for each of the three US market indices is shown in Figure 4, in which we can see a cluster of heightened amplitude in the rate of return at the initial stage and later a declining trend in volatility over time.

For the explanatory variables, although all coefficients show a negative correlation between new confirmed cases per day on each of the three stock indices, only one estimate, which explains the relationship between the US confirmed cases and Dow Jones return, is statistically significant with a p-value less than 0.05. Another two coefficient estimates are less significant with a p-value less than 0.1, and the rest of all coefficient estimates are statistically non-significant with a p-value greater than 0.05. This result indicates that although initially, COVID-19 might bring a negative shock to US stock performance, in the long run, new daily cases exert a sluggish and non-significant impact on market return. This finding also corresponds to the empirical findings of COVID-19's long-term impact on the US stock market analyzed in previous section 3.2.

**Table 4.** ARMA-GARCH model estimation results, variance equation

Variables	Nasdaq		S&P 500		Dow Jones	
	(1)	(2)	(3)	(4)	(5)	(6)
	New confirmed cases					
The US	-0.0161 (0.0440)		-0.0609** (0.0311)		-0.0848*** (0.0247)	
Global		-0.0163 (0.0647)		-0.0485 (0.0481)		-0.0922** (0.0405)
	ARCH					
ARCH (-1)	0.2364*** (0.0510)	0.2396*** (0.0509)	0.2540*** (0.0484)	0.2778*** (0.0518)	0.2606*** (0.0577)	0.2828*** (0.0579)
GARCH (-1)	0.7203*** (0.0527)	0.7166*** (0.0517)	0.7028*** (0.0427)	0.6726*** (0.0480)	0.6910*** (0.0522)	0.6837*** (0.0488)
Constant	-11.1435*** (0.5023)	-11.0904*** (0.8305)	-11.0863*** (0.3319)	-10.9607*** (0.5967)	-10.7718*** (0.2899)	-10.6203*** (0.4802)

#### 4. Discussion

This result which shows an initial negative and volatile response to COVID-19 and then a sluggish influence is aligned with a previous study done by Vasileiou, who explained the phenomenon in two ways [13]. The most common explanation is that the initial decline in the stock market can be the result of sudden and unexpected negative economic consequences caused by the pandemic. Within three months of the COVID-19 outbreak, the US issued travel restrictions as well as stay-at-home orders, which dramatically reduced consumption and economic activities that propelled the stock return to decline. When stimulus packages, vaccines, and reevaluated restrictions were employed in later months, the market slowly recovered from the initial shock. Another explanation proposed by Vasileiou is that behavioral factors such as risk aversion and fear can also cause market fluctuation [13]. Decker and Schmitz proved that "health risk is positively associated with risk aversion" [14]. Therefore, when COVID-19 spreads, we assume that health risks, fear of the new virus as well as risk aversion increase, which in turn leads to the stock market price decline. However, when the vaccine was released in August 2021 and people became more familiar with COVID-19 treatments, people's uncertainty, fear, and risk aversion decreased.

However, the number of COVID-19 cases was examined as explaining variables in this paper. There are other more specific factors related to COVID-19 that can be used to analyze the pandemic's

impact on stock performance. For instance, the level of cultural uncertainty avoidance proposed by Ashraf and trust levels between citizens and government proposed by Engelhardt et al. can all be additional factors contributing to market return analysis in response to COVID-19 [5, 15]. This study complements existing literature by providing a US-specific empirical analysis during a more representative and updated time frame as compared to existing literature, which holistically covered the US stock market performance from the initial shock of COVID-19 until the turning point by the end of 2021. The time series analysis details both the short-term and long-term impact of COVID-19 on the US stock market in days, which allows further analysis to incorporate more potential explanatory variables including monetary policies, vaccination status, and other factors during an even more specific time frame within data range of this study. Thus, future studies can refer to this quantitative and empirical time series analysis to provide a more holistic qualitative analysis of the pandemic impact on the US stock market which incorporates country and culture-specific elements.

## 5. Conclusion

In this paper, we employed VAR and ARMA-GARCH models to examine the time series impact of the COVID-19 pandemic on the US stock market from 31 December 2019 to 30 December 2021. Using domestic and global new COVID-19 cases per day and stock market returns data from Nasdaq, S&P 500, and Dow Jones, we find that the US stock markets show an initial negative response to the increase in COVID-19 in both global and domestic confirmed cases. The negative response was especially dominant between 40 to 60 days after the initial pandemic outbreak. Then market returns exhibit waves of dynamic fluctuations until it dies down after around 200 to 300 days. Together our findings suggest that COVID-19 reacts strongly during the early months of COVID-19, but later exerts non-significant influence over the US stock market performance when a longer period after the initial pandemic outbreak.

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