Dynamic changes in US Financial Markets under the COVID-19 Pandemic

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Abstract. Covid-19 disrupted people's lives and the world's economic activities in major ways. The pandemic affected, businesses, companies, and investors in the stock market. This paper aims to how normalized Covid-19 affect the United States stock market by analyzing three major US stock markets: S&P500, NASDAQ, and DJIA. The aim was to examine the effect on stock market's return and volatility. To analyze the impact of the pandemic, vector autoregression models (VAR) as well as the ARMA-GARCH-X model were used. Impulse response function graph from the VAR model revealed that the pandemic did increase or decrease the stock market returns of either of the indices. However, fluctuations in returns were shown to be higher during the early period but faded with time. The ARMA-GARCH-X model however reported that the pandemic only influenced the volatility of S&P500 returns only while the other two markets were not affected. Conclusion drawn from the study is that the pandemic influenced the stock markets in the early days but its influence tapered down due to normalization of the pandemic in the mind of investors. Government responses to the pandemic as well as the introduction of vaccines could also serve to raise investor's confidence thus reducing the influence of the pandemic on the stock market.

Keywords: US financial market, VAR, ARMA-GARCH, COVID-19.

1. Introduction

The advent of the Covid-19 pandemic caught the world by surprise. The impact of the pandemic was felt throughout the world. Many researchers argued that the pandemic was a black swan as it was a rarity and had severe negative consequences throughout the world [1-3]. A black swan can be considered as an event whose probability of occurrence is very low but its impact is severe. Often it is difficult to plan for black swans as these events are difficult to predict as to when and how they will happen. In that light, due to the pandemic black swan, world economies were affected as governments and other agencies tried to battle the disease while trying to balance their economies. Government and other government-authorized organizations instilled measures such as mandatory lockdowns which led to adverse economic effects. Supply chains were disrupted, businesses closed, countries' GDP fell and most stock markets were significantly impacted especially in the early days of the pandemic. For example, oil prices plummeted sometimes during the pandemic due to drastic decline in demand [4]. Additionally, the US market's circuit breakers had been triggered four times leading to many investors incurring huge losses in a short time. Overall, many stock market indices in different economies were negatively impacted by the pandemic especially in the short term while only a few indices registered positive returns [5].

Several recent researches have linked the financial market performance to the pandemic. Most researchers agree on the influence of the pandemic on the stock market returns. However, there is a mixed conclusion regarding the impact of government intervention with regard to the pandemic on the stock market which will be discussed in this section. This research has also tried to understand and explain investors' behaviors in the stock markets during pandemic period. For instance, Umar and Gubavera studied the coherence between the panic levels caused by the covid-19 and the volatility levels of the exchange rates [6]. The study included the Great Britain Pound, the Chinese currency Renminbi, and the Euro as well as major cryptocurrencies. The study found that there was coherence between the panic levels and the currencies. This implied that the currencies movements was synchronized with the pandemic level thus showing that the pandemic was negatively impacting the financial markets.

Bradley and Stumpner in their article manage to put a unique perspective on the effect of covid-19 on the markets [7]. The authors examined over 5000 of the biggest companies in the world. They explain that the covid-19 took the industries through a four-phase journey. In the early phase, news regarding the covid-19 was all about doom and gloom which led to huge market losses. However, around mid-March, governments around the world began to provide stimulus packages in order to boost their economies. This began shifting the tide. Companies began to recuperate the losses they had incurred which subsequently improved their stock market prices. However, the recovery was uneven. Some companies managed to incur profits while others continued to suffer losses thus creating a drift between companies performing well and those performing dimly. This drift only continued to widen throughout the year. However, by the end of the year, those companies which performed below their normal began to recover their losses as well. This is phase 4 and much of the recovery was attributed to optimistic views due to the introduction and availability of vaccines for Covid-19. By this time, some companies were far off with regard to the amount of success and profits they had gained thus leading to groups of companies that massively profited from the crisis while the rest suffered.

Al-Alwadhi et al. conducted a study to determine the effect of daily growth in covid-19 cases and death on the Chinese stock market returns [8]. Empirical results revealed that growth in the number of cases and death related to the pandemic significantly negatively impacted the returns of stocks in the Chinese market. Additionally, the researchers found that stocks of companies with large market capitalization were more negatively impacted compared to their counterparts. Also, it was found that the pandemic affected different sectors of the economy in different ways. These results are backed by Erdem [9] and O'Donell et al. [10] who found that pandemic was negatively associated with negative returns but positively associated with volatility of the stocks. Erdem's research however sorts to study the effect of pandemic with the freedom index of the country in mind. The researcher added that the adverse effects were less for "freer" countries as compared to less "free" countries. However, this effect was attributed less to their free nature and more to how robust their financial systems were. Using the S&P500 as the proxy for US stock markets, Albulescu also found that the Covid-19 pandemic increased the volatility of stock markets in the United States [11]. The results also revealed that the volatility of the markets was more sensitive to global reports as compared to the domestic national reports implying that international death cases caused more volatility in US stock markets compared to domestic cases. Zaremba et al. on the other hand found that government interventions increased stock market volatility [12].

Contradictory results also exist. Using a TVP-VAR model, Liu and Lee found that spread of the novel coronavirus in America had a positive influence on crude oil and stock market returns [13]. The researchers explained this behavior by stating that it could be that due to the increased risk, the investors required higher risk premiums which translated to higher returns. However, maybe the increase in stock returns could be explained by some of the measures which in the first place led to a decline in economies. Narayan et al. found that government responses to Covid-19 had significantly positive impacts on stock market returns [14]. Using regression models controlling for other factors that have been found to influence stock market returns, the researchers focused their study on G7 countries. They concluded that lockdown measures travel bans and stimulus packages were all significant in cushioning the impact of covid-19 on the stock markets. Studying other measures initiated by the government to curb the spread of covid-19, Chang' and Zheng' found that these measures were positively related to the stock markets [15]. The researchers explain that the reason for this is that these measures raise investors' confidence in the government's ability to deal with the pandemic and subsequently gain an optimistic view of future economic conditions hence the increase in market returns. A sentiment that is backed by Khan's et al. found that over a longer period stock market returns in China bounced back due to investors' confidence as a result of governments response to the pandemic [16]. In the early period, however, Khan et al. explain that investors do not react to news of pandemic until the reality of transmission is confirmed.

From the literature, it can be noted that the impact of the pandemic on the stock market is mixed. While most researchers conclude that the pandemic had a significantly negative impact on the stock markets, a few research reveal that there were positive effects. The purpose of this research is to contribute to the body of knowledge by studying the dynamic changes in the United States financial market under Covid-19. The study hypothesis is that covid-19 has reduced market returns while increasing volatility. To test this claim, a VAR and ARIMA-GARCH-X models are used.

The following sections of this paper are organized as follows: Section 2 of the paper will be the research design which will include a discussion on the data sources, stock returns, and global cases, and a theoretical discussion of unit root test, VAR model and the ARMA-GARCH model. Section 3 of the paper will include empirical results and discussion. This section will include estimation of VAR model, ARMA model, and the ARMA-GARCH model. Section 4 is the discussion and implication and section 5 is the conclusion. Finally, References are presented in section 6.

2. Research Design

2.1 Data sources

Data used in this model was collected from Choice Finance. Daily data were collected for the period between 24th January 2020 to 29th July 2022. The data collected were for the Dow Jones Industrial Average (DJIA), the S&P500, and the NASDAQ. Adjusted closing prices were used for this analysis. Additionally, data for the global Covid-19 death cases were collected for the same period and same frequency from the same website.

In order to work with the data, log returns for the stock market prices were calculated using the formula:

$$Log\ Yield_t = \ln\left(\frac{Y_t}{Y_{t-1}}\right) \quad (1)$$

2.2 Unit Root test

Var models require the series used to be stationary at level or on first differencing. Therefore, the time series variables must be examined for stationarity. Said and Dickey provided a method to test for unit root in an ARIMA series whose order of p and q is unknown [17]. The method known as augmented Dicky Fuller test can be summarized using the following formula:

$$\Delta Y_t = \alpha + \delta Y_{t-1} + \sum_{i=1}^{k} \beta_i \Delta Y_{t-i} + \epsilon_t \quad (2)$$

Stationarity can be inferred using the following hypothesis.

$H_0: \delta = 0$; presence of unit root/non-stationary series.

$H_1: \delta < 0$; stationary series.

When performing the unit root test using the ADF test, the decision criteria is that when the p-value is less than the 5 percent significance level the null hypothesis is rejected and the series is considered stationary.

2.3 VAR model

Sims popularized the Vector autoregressive models (VAR) in econometrics [18]. The model was developed as a natural generalization of univariate Autoregressive models. Brooks explains that a VAR model can be considered a systems model; that is the model has more than one dependent variable. In the VAR model, the number of equations will be equal to the number of endogenous variables. However, this does not mean that exogenous variables cannot be added to explain variations in endogenous variables. A simple way to depict a VAR model is a bivariate model. Here, there are only two endogenous variables leading to two equations. The number of lags, K, should be the same for all variables. The model is depicted in the formula below.

$$\begin{cases} y_{1t} = \beta_{10} + \beta_{11}\, y_{1t-1} + \cdots + \beta_{1k} y_{1t-k} + \alpha_{11}\, y_{2t-1} + \cdots + \alpha_{1k}\, y_{2t-k} + u_{1t} \\ y_{2t} = \beta_{20} + \beta_{21}\, y_{2t-1} + \cdots + \beta_{2k} y_{2t-k} + \alpha_{21}\, y_{2t-1} + \cdots + \alpha_{2k}\, y_{2t-k} + u_{2t} \end{cases} \tag{3}$$

Where k is the lag and u is the white noise disturbance.

As noted from the equation, the system could be expanded to include more than 2 variables. Other terms such as MA terms or exogenous variables could also be included in the model thus making the model advantageous in terms of flexibility. However, a disadvantage arising from this is the number of coefficients to be estimated is many and there is a challenge in choosing the number of optimal lags to be used in the model. Too many lags could lead to loss of degrees of freedom, multicollinearity, and estimation of many statistically insignificant coefficients. Too few lags could lead to misspecification due to serial correlation of error terms. Therefore, it is imperative to calculate the optimal lag length to be used in the model. This could be done through different criteria with the most commonly used being the Akaike and Schwartz information criteria. The optimal lag length is chosen where the information criteria are minimized. For VAR the multivariate version of the Akaike information criteria will be used. The criteria could be defined as follows:

$$MAIC = ln\,(|\Sigma|) + \frac{2k}{T-p} \tag{5}$$

Where k is the lag length and T-p is the number of observations used in estimation of the model.

Since the equations are a set of different univariate AR models, equation to equation OLS is used to estimate the coefficients of the model. Once the coefficients are estimated, a diagnostics check will have to be performed to ensure the model is viable. In this model, the diagnostic that will be considered is the stability test which looks at whether the eigenvalues are found within the unit root.

Once the model has been estimated, the impulse response function will be constructed. The impulse response function (IRF) will be used to study how the different endogenous variables within the VAR models interact with each other [18]. The irf can be visually depicted to show how the variables respond to shocks introduced into the system.

2.4 ARMA-GARCH model specification

Classical linear regression models and ARIMA models hold the assumption that the variance of the errors should be constant and the relationship linear [19]. For instance, financial asset return series have certain attributes that make them non-linear and with time-varying volatility. Financial time series can have linear returns but variances that are not linear. Additionally, the series is leptokurtic, and exhibit volatility clustering and leverage effects where volatility will rise more for price falls than price increase. All these characteristics are motivations for the use of ARCH models which take into account heteroskedastic variances. However, since ARCH models can often produce negative coefficients which are nonsensical when examining variance, the GARCH model is used. GARCH models do not produce negative coefficients. Unlike ARCH, GARCH model is parsimonious. In its simplest form, the model can be defined as follows:

$$\begin{cases} Y_t = a + X_t + u_t \\ h_t = \alpha_0 + \beta_1 h_{t-1} + \phi_1\, u_{t-1}^2 \end{cases} \tag{6}$$

where equation 1 represents the mean equation and two is the variance equation. The mean equation can be any model such as a normal classic regression model or an ARIMA model. This simple model is the GARCH (1,1) model. The variance equation consists of the mean conditional variance represented by α_o, the lagged values of the variance represented by h_{t-1} and the return information represented by u_{t-1}^2. h_{t-1} is also referred to as the Garch term and u_{t-1}^2 is referred to as the arch term. The variance equation can be extended to include higher lags for the arch terms and GARCH terms and be defined as follows:

$$h_t = \alpha_0 + \beta_1 h_{t-1} + \cdots + \beta_p h_{t-p} + \phi_1 u_{t-1}^2 + \cdots + \phi_q u_{t-q}^2 \quad (7)$$

Additionally, an external explanatory variable can be added to the model. In this case, confirmed infection cases in period t can be added as the exogenous variable in the model.

3. Empirical Results and Analysis

3.1 VAR Estimation Results

3.1.1 Stationarity test

As stated earlier, VAR models require the series to be stationary at level or first difference. Therefore, the ADF test was performed and the results are depicted in Table 1 below.

Table 1. ADF test

Variables	t-statistic	p-value
	Price	
NASDAQ	-0.959	0.9494
S&P 500	-1.426	0.8531
DJI	-1.860	0.6753
	Yield	
NASDAQ	-17.445	0.0000***
S&P 500	-17.077	0.0000***
DJI	-16.562	0.0000***
	Covid-19 pandemic, new confirmed cases	
The global	-7.875	0.0000***

Results of the ADF test report that the NASDAQ, S&P500, and DJI price series have p-values that are more than the 5 percent significance level implying non-stationarity of the series. However, the return series for the same variables report p-values that are less than 0.0001. Since the p-values are less than the 5 percent significance level, the null hypothesis is rejected. This implies that all three series are stationary. The log transformed series of global cases is also reported to have a probability value (p-value < 0.0001) that is less than the 5 percent significance level implying stationarity of the series.

3.1.2 Optimal Lag Selection and Model Stability

Once the series is confirmed to be stationary, the optimal lag models are estimated using the varsoc command in Stata. The results of the process are displayed in Table 2 below.

Table 2. VAR model identification

Lag	LL	LR	df	p	FPE	AC	HC	SC
0	5594.55				1.8e-13	-17.976	-17.965	-17.9475
1	5899.59	610.08	16	0.000	7.2e-14	-18.9054	-18.85	-18.7629
2	5982.75	166.33	16	0.000	5.8e-14	-19.1214	-19.0217	-18.8648*
3	6029.61	93.717	16	0.000	5.3e-14	-19.2206	-19.0766	-18.85
4	6062.38	65.532	16	0.000	5.0e-14	-19.2745	-19.0862*	-18.7899
5	6091.24	57.715	16	0.000	4.8e-14	-19.3159	-19.0832	-18.7172
6	6112.77	43.057	16	0.000	4.7e-14	-19.3337	-19.0567	-18.621
7	6133.68	41.838	16	0.000	4.6e-14*	-19.3495*	-19.0282	-18.5227
8	6142.31	17.247	16	0.370	4.8e-14	-19.3257	-18.9601	-18.385
9	6165.34	46.062*	16	0.000	4.7e-14	-19.3484	-18.9384	-18.2936
10	6175.66	20.648	16	0.192	4.7e-14	-19.3301	-18.8758	-18.1613
11	6181.24	11.156	16	0.800	4.9e-14	-19.2966	-18.798	-18.0138
12	6189.36	16.24	16	0.436	5.0e-14	-19.2713	-18.7284	-17.8744

Using the AIC criterion, the number of optimal lags is 7.

Once the model has been estimated, the stability of the model is checked. Using the post-estimation command varstable, the stability graph in the Figure 1 below is produced.

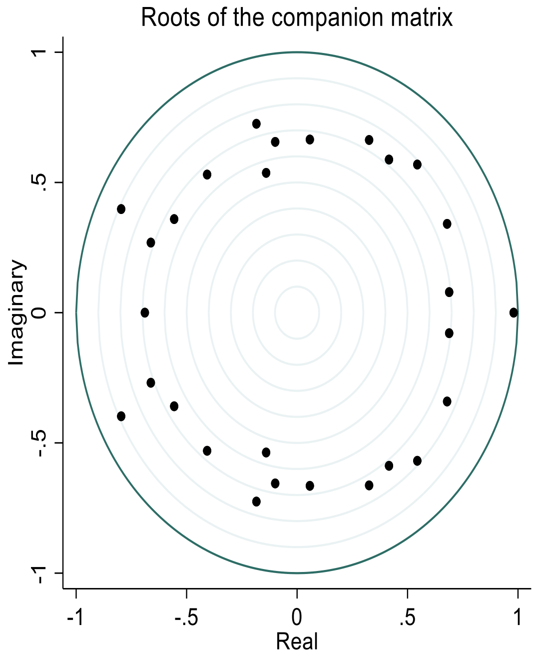

Figure 1. Unit-circle test

For the model to be considered stable, all the eigenvalues represented by the dots should only exist within the unit circle. As seen from the graph all the eigenvalues are found within the unit circle thus confirming that the model is stable.

3.1.3 Impulse response graph

As stated earlier the impulse response graph was constructed. Here the number of global cases is considered as the impulse and the stock market variables are the responses. Results of the impulse response function are displayed in Figure 2 below:

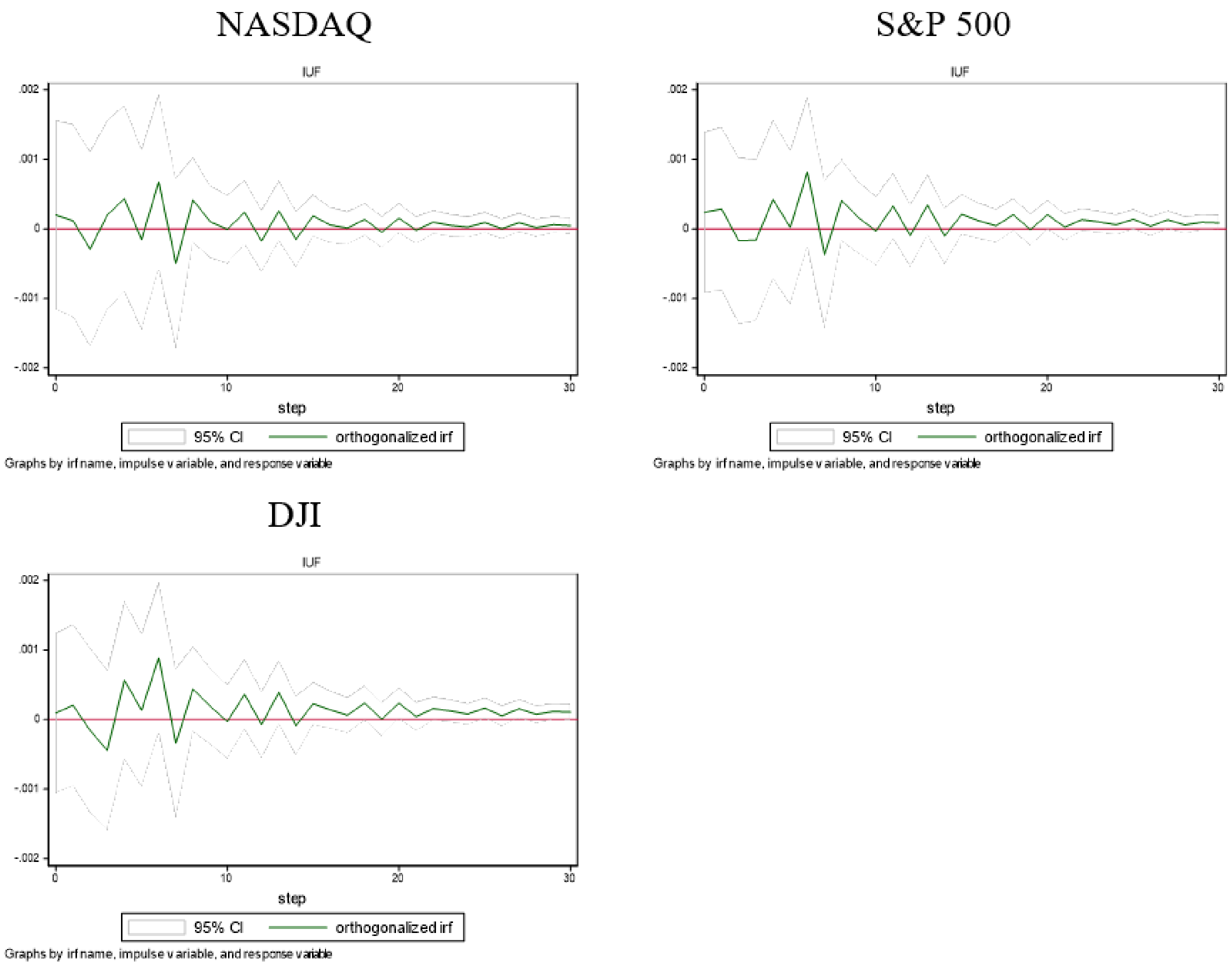

Figure 2. Impulse and response

The impulse response function reveals that the number of reported daily infections did not have any significant impact in terms of increasing or reducing the returns of the series. However, it can be noted that the covid-19 cases affect the volatility of the return series within the early periods. However, its effect taper down with increase in the number of days thus showing that current covid-19 infection cases slightly increase the volatility of the return series but the impact tapers down with time.

3.2 ARMA Order Identification

GARCH uses MLE to estimate the mean and variance equations simultaneously. In this case, the ARMA model with the global cases added as the exogenous variable will be used to model the three series. To find the proper ARMA model for the data, the ACF and the PACF are used to find the optimal AR and MA lags. A correlogram of the ACF and PACF is depicted in Figure 3 below:

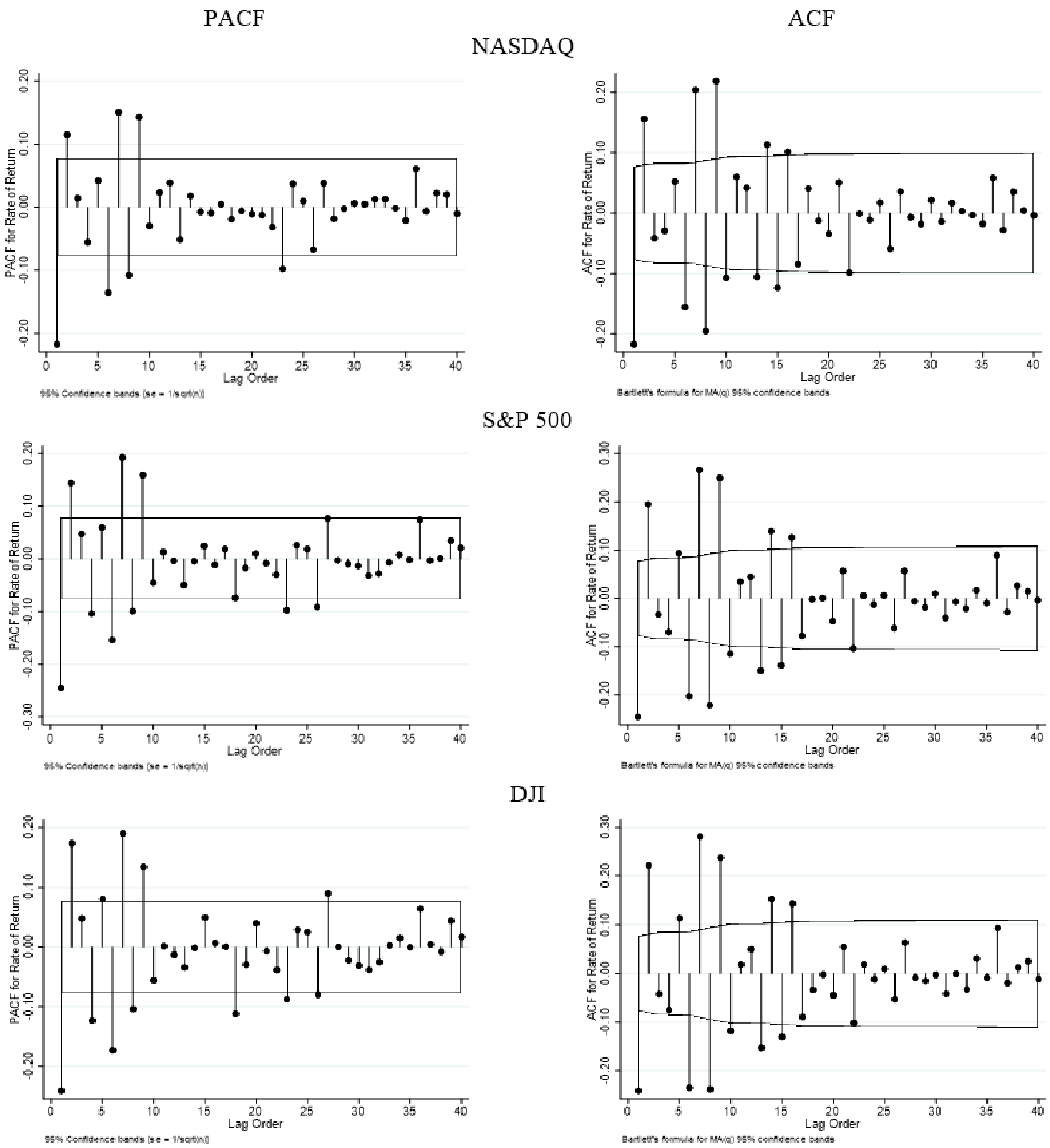

Figure 3. PACF and ACF

The models show that several lags are significant. However, it is known that a parsimonious model is better. Therefore, in the spirit of parsimony, all the models chosen are depicted by ARMA (2,2) models. This is because all the PACF correlograms have lags 1 and lag 2 as significant therefore indicating that AR (2) process can be used. Additionally, the ACF correlograms depict the same structure as the PACF correlograms. In the same manner, the first two lags are chosen as the lags to be used in the model indicating that an MA (2) process is relevant in the model.

3.3 ARMA – GARCH-X Model Estimation

Results of the ARMA-GARCH-X model are presented in Table 3 below.

Table 3. ARMA-GARCH-X model estimation results

	(1) NASDAQ	(2) S&P 500	(3) DJI
	New confirmed cases		
The global	0.0008	0.0008**	0.0005
	(0.0005)	(0.0003)	(0.0003)
	GARCH (1, 1)		
ARCH (-1)	0.1673***	0.2173***	0.2224***
	(0.0371)	(0.0388)	(0.0423)
GARCH (-1)	0.8072***	0.7520***	0.7354***
	(0.0397)	(0.0386)	(0.0428)
Constant	-9.6470***	-9.6570***	-9.0437***
	(0.9970)	(0.7002)	(0.6215)

Results of the ARMA-GARCH-X model report the exogenous variable for global infection cases to be insignificant in the NASDAQ and DJIA model. However, it was found to be significant in the S&P500 Garch model. These results show that the covid-19 cases did not influence the volatility of the NASDAQ and DJIA. However, results in points to the fact that the S&P500 volatility was positively influenced by the number of infection cases; that is a 1 percent increase in the number of infection led to an increase in the volatility of S&P500 returns by about 0.08 percent.

4. Discussion and Implication

Results from the analysis reveal that the returns of the three endogenous variables were not impacted by the number of infections globally. The VAR impulse response graph revealed that the returns of the series did not increase or decrease due to shocks created by the pandemic. These results contradict the findings of other researchers who reported that the pandemic cases had a significant influence on the returns of stock markets e.g. [8-13]. For instance, Al-Alwadhi et al., Erdem, Albulesci and O'Donell et al. found that the pandemic influence the stock market returns negatively. [8-11]. Liu and Lee, on the other hand, reported a positive association between increase in infection of Covid-19 and stock market returns [13]. Overall, the markets were found to have been impacted by the virus. When it comes to volatility, the findings of this research are in agreement with those of other researchers. VaR impulse response graph showed that shocks by the number of infections caused significantly low fluctuation in stock returns, especially in the short run. The effect faded with time. However, the GARCH model reveals that global infection cases only impacted the volatility of S&P500 returns. These results agree with those of Erdem and O'Donell et al. who found that global infection cases had a positive association with stock market returns [9-10].

These results show that covid-19 is an important variable to consider when it comes to the stock market. Additionally, the results show that while covid-19 has had an impact on the volatility of stock returns, the impact seems to fade over time. This points to the fact that the world and investors in particular have become normalized to the pandemic. Rather than being perceived within the frame of doom and gloom, the pandemic is now perceived as commonplace and the world has accepted that it is here to stay. Additionally, the rollout of vaccines could also have the impact of raising investors' confidence in dealing with the pandemic. The overall implication is that black swans such as pandemics should be expected to influence the stock markets and financial systems. Therefore, policymakers who are interested in improving the financial systems should come up with policies that will cushion the impact of such events. Additionally, it is imperative for investors to take into consideration how such unexpected events could influence their stock returns. In the same manner, investors should have contingencies planned to protect during certain times.

5. Conclusion

The purpose of this research was to find out how the covid-19 pandemic influenced the financial systems by studying the stock markets in the United States. Three endogenous variables which acted as proxies for the stock markets in the United States were selected and a single exogenous variable was also included. The S&P500, DJIA, and NASDAQ were selected as the endogenous variable and the number of daily infections was used as the exogenous variable to represent the effect of the pandemic on the stock markets. VAR and ARIMA-GARCH models were used for analysis. Results from VAR model revealed that the pandemic did not have a direct influence in terms of increasing or decreasing the stock market returns. However, it is found that the stock markets caused increased fluctuation in the returns, especially in the early periods but the effect diminished with time. The GARCH model revealed that the pandemic only influenced the volatility of the S&P500 returns but not for DJIA and NASDAQ implying that the pandemic increased its volatility. These results both support and contradict the findings of other researchers who reported that increased infection cases impacted the stock market returns mostly negatively and that almost certainly it increased the volatility of the stock market returns. All in all, the pandemic is an important variable to consider when evaluating the stock markets. Policymakers and investors should learn from this and take caution by setting procedures to cushion the effect of any other future black swan event such as another pandemic.

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