EFFECT OF COVID-19 ON THE UNITED STATES STOCK MARKET: AN EMPIRICAL STUDY

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ABSTRACT

In this study, we investigate the effects of the COVID-19 pandemic on the daily returns, volatility, and trading volume for the DOW, S&P 500 and NASDAQ on the US stock market. In addition, we examine the pandemic effect on the relationships between market volatility and market returns and trading volume. The daily data used was over the period January 1, 2019 to December 31, 2020. Results from the time series intervention analysis showed a significant positive impact of the pandemic on volatility and trading volume for the DOW, S&P 500, and NASDAQ. Furthermore, the onset of the pandemic caused a significant sharp drop in the returns over a two-week period. After this period, the markets recovered and the returns during the pandemic were significantly higher than the returns before the pandemic. Also, the pandemic affected the relationships that existed between volatility and returns for the DOW and SP 500. In addition, it had an effect on the relationship between volatility and volume for the NASDAQ and S&P 500.

INTRODUCTION

The coronavirus (COVID-19) pandemic has created drastic negative impacts on the economic activity in the US and in countries around the world. The COVID-19 crisis has affected health, employment, GDP, the hospitality industry, stock markets and other sectors of the economy here in the U.S and globally. The pandemic has reduced consumer spending, particularly in hotels and restaurants, and disrupted the supply chain. Also, there was a substantial decline in consumer demands for goods and services. The pandemic has affected adversely the airline industry and tourism and created a global economic crisis. Public health measures to contain the spread of the coronavirus have caused severe economic downturns and a substantial increase in unemployment.

While there is ample research on the effect of the pandemic on the economy, few studies have dealt with the effect of the pandemic on the stock markets. In this study, we employ time series analysis to investigate the effect of the COVID-19 pandemic on stock market volatility, trading volume, and returns for the NASDAQ, S&P 500, and the DOW Jones Industrial Average.

LITERATURE REVIEW

Chernick et al. (2020) evaluated the fiscal effect of the COVID-19 pandemic on revenue in 150 US cities. The authors provided estimates of shortfalls in revenue for fiscal year 2021 as compared to the forecast prior to the COVID-19 recession. The study considered revenue forecasts for two scenarios, less severe and more severe. It predicted a shortfall in revenue of 5.5% and 9% for the less severe and more severe scenarios. Some cities that were hardest hit faced a shortfall of 15% or more.

He et al. (2020) investigated the effect of COVID-19 on spill-overs in stock markets. The analysis, using t-tests and Mann-Whitney tests, on daily returns in China, Italy, South Korea, France, Spain, Germany, Japan, and the United States showed that the COVID-19 pandemic had negative short-time effects on the stock market returns. In addition, COVID-19 had spill-over effects on stock markets of other countries.

Shapiro (2020), in a research study from the Federal Reserve Bank of San Francisco, investigated the effect of COVID-19 on inflation in the US. The author reported that personal consumption expenditures (PCE) were about a percentage point below the 2% target set by the Federal Reserve. Data showed that the drop in inflation was due to a substantial decline in consumer demands for goods and services.

Sattar et al. (2020) investigated the effect of COVID-19 on stock market indexes of different countries. The authors used a log-log regression model relating log market index to log number of COVID-19 cases. Data obtained were from January 1, 2020 to March 31, 2020. The countries studied included China, USA, UK, Japan, Germany, Hong Kong, Russia, and India. For all indices, there was a negative relationship between the log number of COVID-19 cases and log market index.

Geert et al. (2020) studied the effect of COVID-19 on the US economy. Their investigation revealed that two thirds of the decline in the GDP during the first quarter of 2020 was caused by a decline in aggregate demand. On the other hand, two thirds of the decline in the GDP in the second quarter of 2020 was caused by a decline in aggregate supply. The authors' analysis predicted a slow recovery due to the supply shock.

Andrea et al. (2020) studied the effects of the COVID-19 pandemic on macroeconomic and financial uncertainty and the consequence of uncertainty on key economic variables. The model used for the analysis was the heteroskedastic vector autoregression (VAR). Results of the analysis indicated that COVID-19 contributed to an increase in macroeconomic and financial uncertainty, which caused a downturn in the economic and financial conditions. However, it was determined that the contribution of uncertainty on the economic downturn was small compared to the effects of other factors attributable to the COVID-19 pandemic.

Gibson and Olivia (2020) investigated the effect of the COVID-19 pandemic on life expectancy in Indonesia. The analysis was based on the mortality table, which gives for each age x the probability of death before age x+1. Results of the analysis showed that the indirect effect on life expectancy, as a result of loss in future income, was larger by at least five orders of magnitude than the direct effect due to COVID-19 related deaths. The effect of COVID-19 on poverty was spatially heterogeneous. As expected, the increase in poverty was higher in provinces that had lower initial poverty rates.

Jelilov et al. (2020) examined the relationship between stock market returns and inflation in Nigeria, while controlling for the effect of the COVID-19 pandemic. The authors used the generalized conditional heteroscedasticity (GARCH (1,1)) model in their analysis. Results of the analysis on daily data from February 27, 2020 to April 30, 2020 revealed that Covid-19 increased market volatility and had a negative effect on returns. In addition, inflation, in the presence of COVID-19 had a negative effect on returns.

Schmitz et al. (2020) estimated that the cost to producers of ethanol, corn, gasoline, and oil in the US, due to the COVID-19 pandemic, was 176.8 billion dollars in 2020. The cost for oil producers alone was 151 billion dollars in the US and 1055.8 billion dollars worldwide. When the unemployment effect is taken into consideration, the cost estimate was 1266.9 billion dollars.

Rababah et al. (2020) examined the effect of the COVID-19 pandemic on the financial performance of Chinese listed companies. Regression analysis was performed on industries over time (panel regression). Financial performance (ROA) was the dependent variable and the independent variables were the natural log of assets of the company (size), leverage, growth rate, the natural log of total revenues, industry, year, and pandemic period (dummy variable). Results from the analysis showed that the COVID-19 pandemic had a negative impact on financial performance., predominantly for small and medium size companies. Also, the negative effect was industry specific.

Singh and Neog (2020) discussed the economic impact of the COVID-19 pandemic on India's travel and tourism, transportation, stock market, macro-economy, human capital, and trade. The assessment was that India could experience significant economic contraction in the near future as a result of COVID-19. The authors offered policy suggestions to mitigate the health and economic crises.

Moen et al. (2020) examined the effect of the COVID-19 pandemic on unemployment in the United States over the period January through April 2020. There was evidence of an increase in unemployment for all ages and across gender, educational attainment, and race/ethnicity. Young adults and women were especially at risk of being unemployed. Black men with college degrees experienced an increase of 12.4% in unemployment. Individuals in their 50s and 60s with less than a college degree were less likely to become employed, regardless of race.

Von Wachter (2020) studied the long-term effects of the COVID-19 pandemic on unemployment with regard to job losers and labor market entrants in the United States. Measures of the scale of job loss during the pandemic, compared to those from past recessions, indicated that the cost of job loss can reduce earnings for several decades. The predicted losses in lifetime earnings were about two trillion dollars. Furthermore, losses in unemployment could mean a lasting reduction in the employment to population ratio.

Gursoy and Chi (2020) examined the effect of the coronavirus pandemic on the hospitality industry. Study showed that over 50 % of individuals were not willing to dine at a restaurant or stay at a hotel. Also, results of the study indicated that 25% of individuals would feel comfortable with dining at a restaurant and 18% staying at a hotel when testing, tracing and isolating cases in a community improves. A smaller percentage (14% to 17%) will feel comfortable dining at a restaurant or staying at a hotel only when vaccine becomes available. These results suggest that research efforts in behavioral and operational hospitality marketing and management must be directed at determining what factors will make customers return.

Ngwakwe (2020) examined the effects of the COVID-19 pandemic on the SSE Composite Index in China, the Euronext 100 in Europe, and the Dow Jones Industrial Average and the S&P 500 in the United States. Data on stock market performance were gathered 50 days before and 50 days within the COVID-19 pandemic. The before and after stock market mean values were compared using a paired sample t-test. Results of the analysis showed that the Dow Industrial Average had a significant reduction in mean value during the pandemic. However, the Chinese stock market had a significant increase in mean value during the pandemic. There was no change in mean value for the European and S&P 500 markets.

Gruenwald (2020) reported on the impact of the coronavirus pandemic on the world economy in 2020. Forecasts were presented showing a drastic decrease in GDP growth in 2020 for the U.S., Eurozone, China, India, Japan, Russia, and Brazil. In addition, global growth forecast was just 0.4% in 2020 with an increase to 4.9% in 2021.

DATA

Daily market data for the DOW, S&P 500, and NASDAQ were obtained, for the period January 1, 2019 to December 31, 2020, from Yahoo Finance. The time period encompassed the periods before and during the COVID-19 pandemic. The data obtained included daily stock market closing index, trading volume in millions, and the high and low for the day. The range, as a measure of daily volatility, was equal to high – low for the day. Considering the timeline of COVID-19 developments in 2020, the intervention model time T (Equation (1)) for the onset of the effect of the pandemic in the US was taken to be March 2, 2020, the first day in March when the stock market opened.

METHODS

The statistical analysis utilized for this study included time series intervention analysis, time series regression, using the transfer function approach, and the autoregressive conditional heteroscedasticity (ARCH) model. SAS was used in the analysis.

Intervention Analysis

Intervention analysis (Box & Tiao, 1975) is used to study the effect of an intervention on a time series response variable when the time (T) of the intervention is known. The intervention in this case is the onset of the coronavirus pandemic, taken to be March 2, 2020, and is entered in the model as a step function (0 before March 2, 2020 and 1 afterwards). The impact of the intervention on the response variable can be specified in general as

$$wB^b S_t^T , \qquad (1)$$

where, B is the backshift operator, b is the time shift or delay until the impact of the intervention is felt, and w is the impact coefficient and

$S_t^T = \begin{cases} 0, t < T \\ 1, t \geq T \end{cases}$

If the response due to the impact is gradual, the impact can be specified as

$$(wB^b / (1-\delta))S_t^T \quad (2)$$

Where δ is between 0 and 1 (Wei, 2006).

For this analysis, the intervention model that gave the best fit to the data was

$$y_t = x_t + wB^b S_t^T \quad (3)$$

where y_t is the observed series and x_t is the series before the intervention, expressed as an ARIMA process, $\frac{\varphi(B)}{\theta(B)}$ x_t.

ARCH Model

Market volatility, as measured by the error variance, is rarely constant over time. A model incorporating a non-constant error variance over time is called autoregressive conditional heteroscedasticity (ARCH), Engel (1982). The model expresses the residual (η_t) from regression as

$$\eta_t = \sigma_t e_t \quad (4)$$

where σ_t is the standard error at time t, e_t is the independent error, and

$$\sigma^2_t = \Theta_0 + \Theta_1 \eta^2_{t-1} + \Theta_2 \eta^2_{t-2} + . . + \Theta_s \eta^2_{t-s} \quad (5)$$

An extension of the ARCH(s) model is the generalized autoregressive conditional heteroscedasticity (GARCH (r, s)) model (Bollerslev, 1986) where the error variance is expressed as a function of its own lags and the lags of the residuals.

$$\sigma^2_t = \Theta_0 + \emptyset_1\sigma^2_{t-1} + \emptyset_2 \sigma^2_{t-2} + . . . + \emptyset_r\sigma^2_{t-r} + \Theta_1 \eta^2_{t-1} + \Theta_2 \eta^2_{t-2} + . . + \Theta_s \eta^2_{t-s} \quad (6)$$

In general, if the residuals ($€_t$) from regression are auto-correlated, the GARCH model can be expressed as

$$€_t = \delta_1 €_{t-1} + . . . + \delta_p €_{t-p} + \eta_t$$
$$\eta_t = \sigma_t e_t$$
$$\sigma^2_t = \Theta_0 + \emptyset_1\sigma^2_{t-1} + \emptyset_2 \sigma^2_{t-2} + . . . + \emptyset_r\sigma^2_{t-r} + \Theta_1 \eta^2_{t-1} + \Theta_2 \eta^2_{t-2} + . . + \Theta_s \eta^2_{t-s} \quad (7)$$

The portmanteau Q statistics (McLeod and Li, 1983) was used for determining the order of the GARCH or ARCH model. The model that gave the best fit to the data and was used in this study for estimating the daily standard (SE) as a measure of volatility, was the ARCH (1) model. Also, in the ARCH regression, the regression model used included the first difference (return) of the DOW index, the S&P 500 index, or the NASDAQ index as the stationary dependent variable and the first lag of the difference, if significant, as an independent variable.

Time Series Regression

The standard error (SE_t), as an estimate of volatility at time t in days, for the DOW, S&P 500 (SP), and NASDAQ was calculated from the ARCH (1) model, for a given data set. We then studied the effect of SE and range (defined as high – low for the day) on the DOW index and volume, the S&P 500 index and volume, and the NASDAQ index and volume for the periods before and during the Pandemic.

The linear time series regression (transfer function approach) was used to determine the effect of a stationary input series on a stationary output series. It should be noted that the first difference, Δ, was used on the DOW, SP, and NASDAQ indexes in order to render them stationary for the time series analysis.

The model relating a stationary output series y_t to a stationary input series x_i is expressed as

$$y_t = v(B)\, x_t + a_{t,} \tag{8}$$

where $a_{t,}$ is the residual and

$v(B) = w(B)B^c/d(B)$.

Here, $w(B) = w_0 – w_1B - \ldots -w_sB^s$

$d(B) = 1-d_1B- \ldots -d_rB^r$.
and c represents the time delay (or lag) until the input variable x_t produces an effect on the output variable $y_{t.}$

We assume that the input series follows an ARMA process, $\frac{\varphi(B)}{\theta(B)}$ x_t. The function v(B) with its lags is determined from the cross correlations between the white noise input series $\frac{\varphi(B)}{\theta(B)}$ x_t and the filtered output series $\frac{\varphi(B)}{\theta(B)}$ y_t (Wei, 2006).
Once v(B) is identified, one can express a_t in Eq. (8) as

$$a_t = y_t – v(B)\, x_t \tag{9}$$

and identify the appropriate time series model for Eq. (9). With a_t known, one can determine the final model in Eq. (8).

For this analysis, all the time series variables were tested for stationarity using the Phillips-Perron test. Where a variable was not stationary, we used its first difference, which was stationary. Thus, all variables that entered the model were stationary.

RESULTS AND DISCUSSION

Table 1 presents the estimates of the impact of the COVID-19 pandemic on the daily DOW returns, daily trading volume, standard error(SE), and range. The standard error was computed from the ARCH (1) model. Both standard error and range were used as a measure of market volatility. It is seen from Table 1 that the COVID-19 impact (w-estimate from Equation (3)) was positive and significant at the 10% level for the DOW returns and highly significant and positive for volume, SE, and range. The impact of COVID-19 was felt 15 days after March 2, 2020. March 2,2020 or day 293 was taken as time T in Equation (1), the onset of the step function.

Figure 1 shows the sharp drop in the DOW index at about day 293 or March 2, 2020 which lasted about 15 days, after which the DOW started its ascent. The delay or time shift of 15 days agrees with the observation in Figure 1. Also, Figures 2, 3 and 4 clearly show that there was an increase in the series mean for volume, SE, and range during the COVID-19 pandemic. This is in agreement with results in Table 1, which shows that the increase in mean was significant. These results indicate that during the COVID-19 pandemic, the daily market returns, trading volume, and volatility increased significantly relative to their values before the pandemic.

TABLE 1. ESTIMATES OF THE PANDEMIC EFFECTS (W), FROM THE INTERVENTION MODEL IN EQUATION (3)

Variable	w -estimate	Standard Error	t -value	p-value	Time-shift in days
ΔDOW	83.66	48.77	1.72	0.0869	15
Volume	119.81	26.48	4.52	<.0001	0
SE	380.23	24.32	15.63	<.0001	0
Range	279.27	68.86	4.06	<.0001	0

The symbol Δ indicates first difference for stationarity

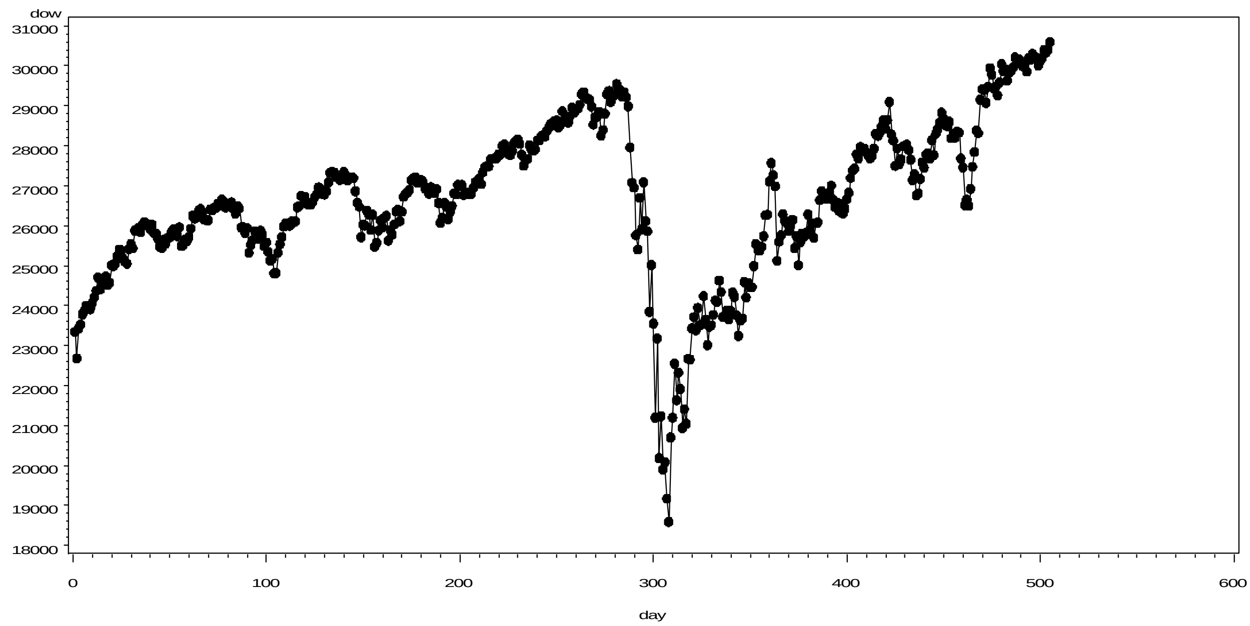

FIGURE 1. PLOT OF THE DOW INDEX OVER DAYS FOR THE PERIOD, JANUARY 1,2019 – DECEMBER 31, 2020.

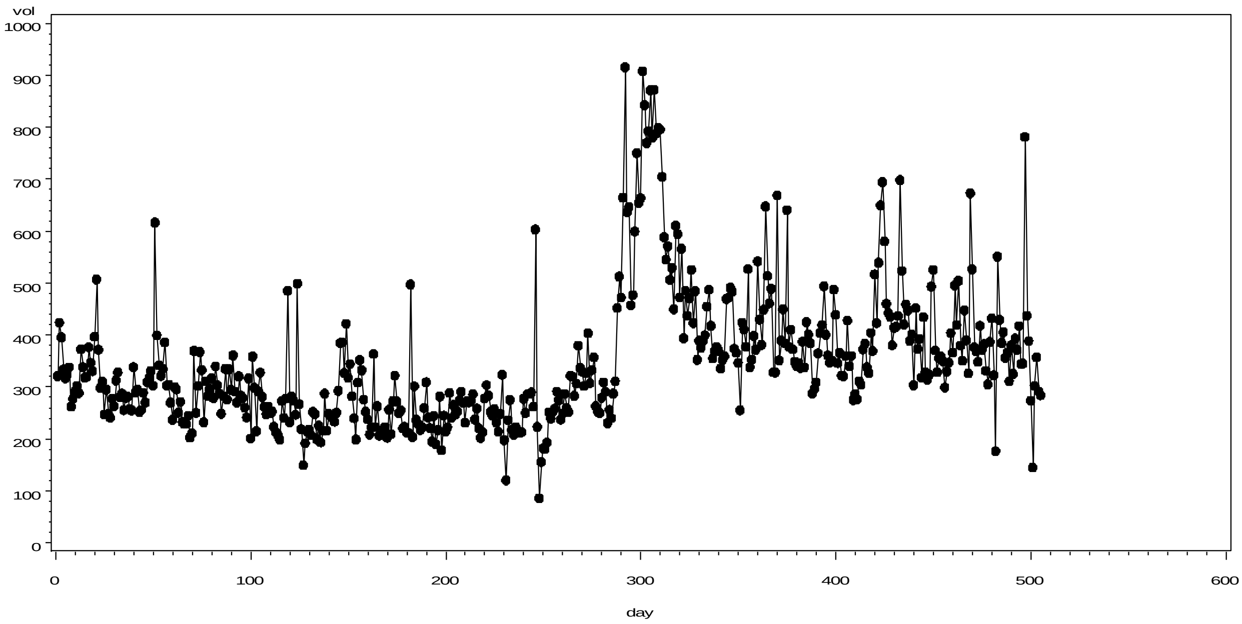

FIGURE 2. PLOT OF THE DOW TRADING VOLUME OVER DAYS FOR THE PERIOD, JANUARY 1, 2019 – DECEMBER 31, 2020.

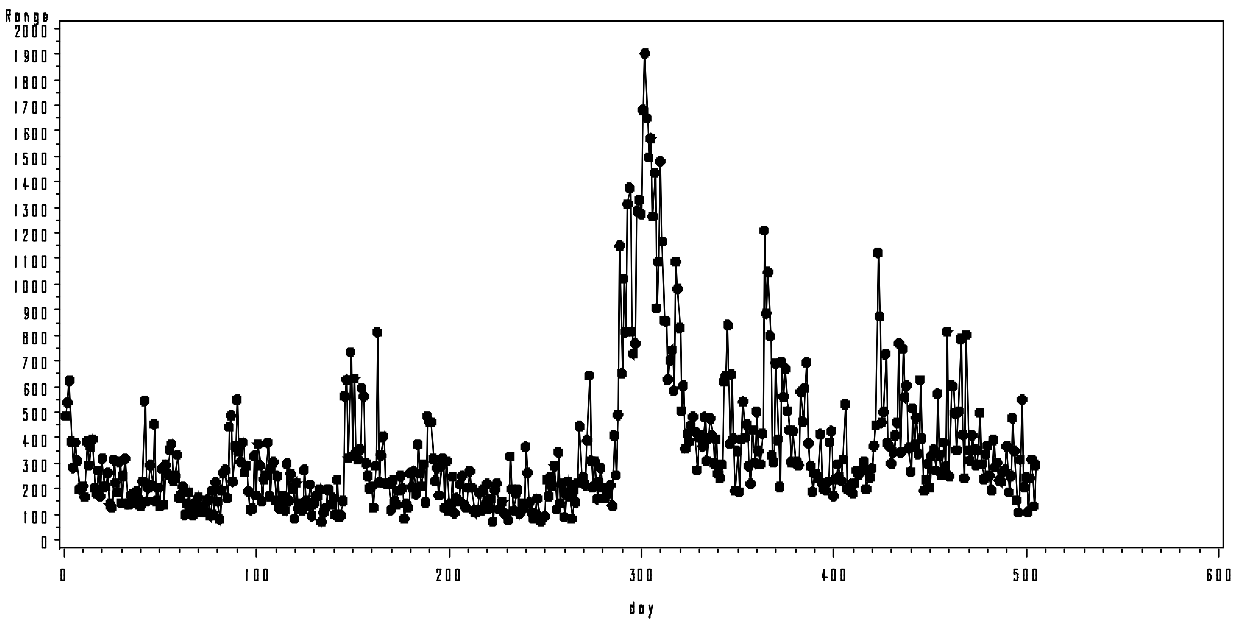

FIGURE 3 PLOT OF THE DOW RANGE OVER DAYS FOR THE PERIOD, JANUARY 1, 2019 – DECEMBER 31, 2020.

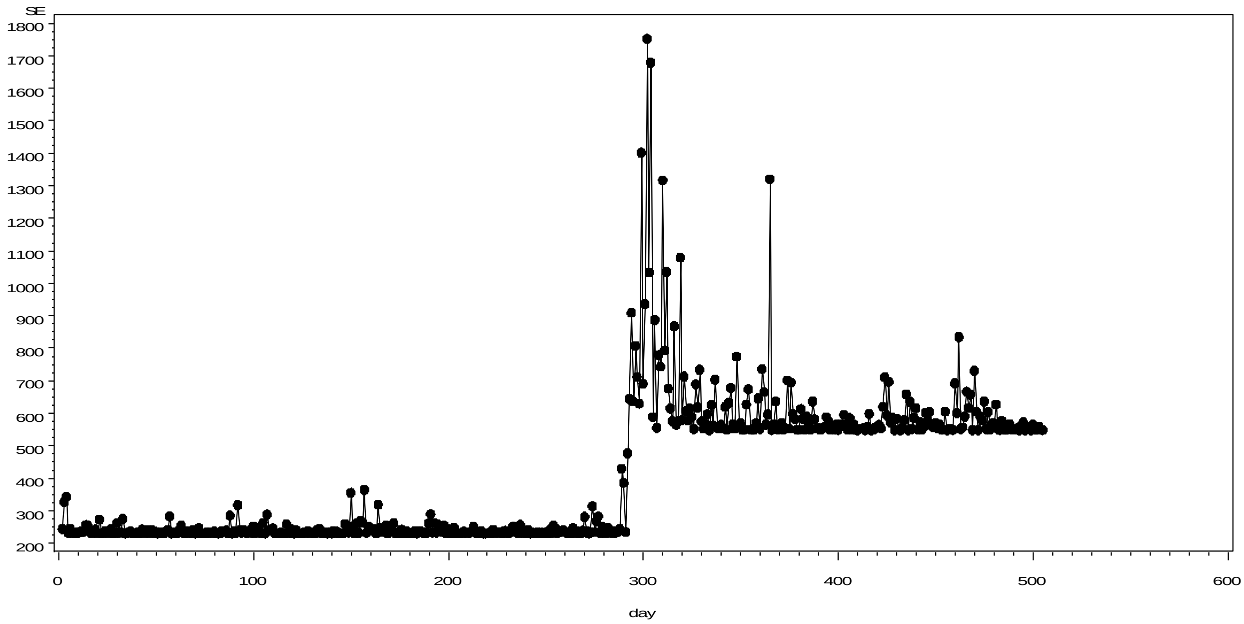

FIGURE 4. PLOT OF THE DOW STANDARD ERROR OVER DAYS FOR THE PERIOD, JANUARY 1, 2019 – DECEMBER 31, 2020.

Table 2 shows the effects of the pandemic on the daily NASDAQ returns, trading volume, and volatility. It is seen that the means of returns, volume, SE, and range increased significantly during the pandemic. As in the DOW case, the impact on the NASDAQ returns was felt 15 days after the onset of the Pandemic. These results are in agreement with the trends over days in Figures 5,6,7 and 8. Figure 5 shows an increase in the rate of growth of the NASDAQ after the drop as compared to the period before the pandemic. Also, the means of the series in figures 6, 7, and 8 were larger during the pandemic period as compared to the period before the pandemic.

TABLE 2. ESTIMATES OF THE PANDEMIC EFFECT (W), FROM THE INTERVENTION ANALYSIS MODEL IN EQUATION (3)

Variable	w -estimate	Standard Error	t -value	p-value	Time-shift in days
ΔNASDAQ	30.58	10.50	2.91	0.0038	15
Volume	1971.70	103.96	18.96	<.0001	0
SE	124.10	3.17	39.11	<.0001	0
Range	110.69	19.95	5.55	<.0001	0

The symbol Δ indicates first difference for stationarity.

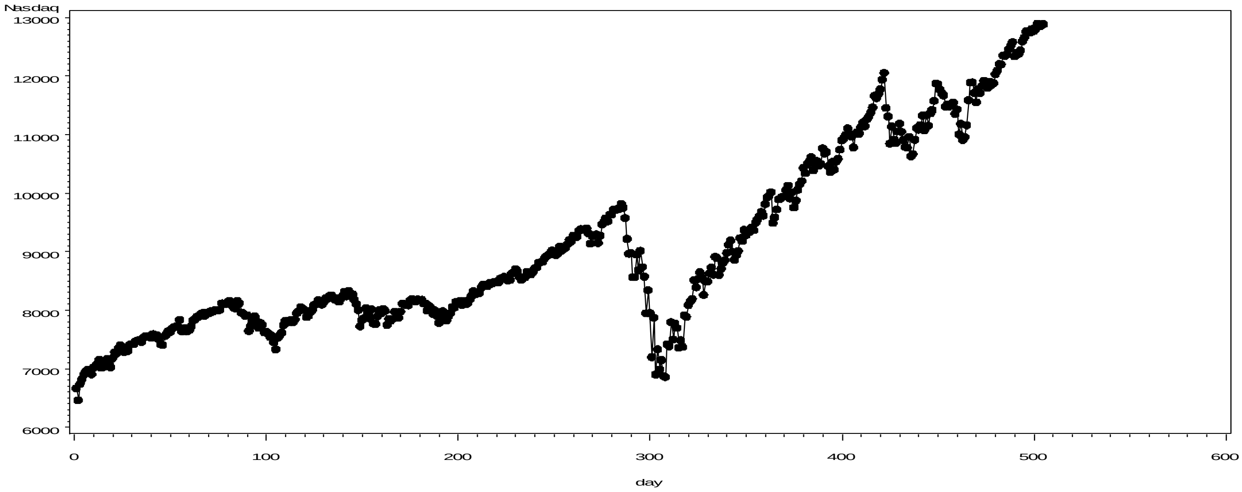

FIGURE 5. PLOT OF THE NASDAQ INDEX OVER DAYS FOR THE PERIOD, JANUARY 1, 2019 – DECEMBER 31, 2020.

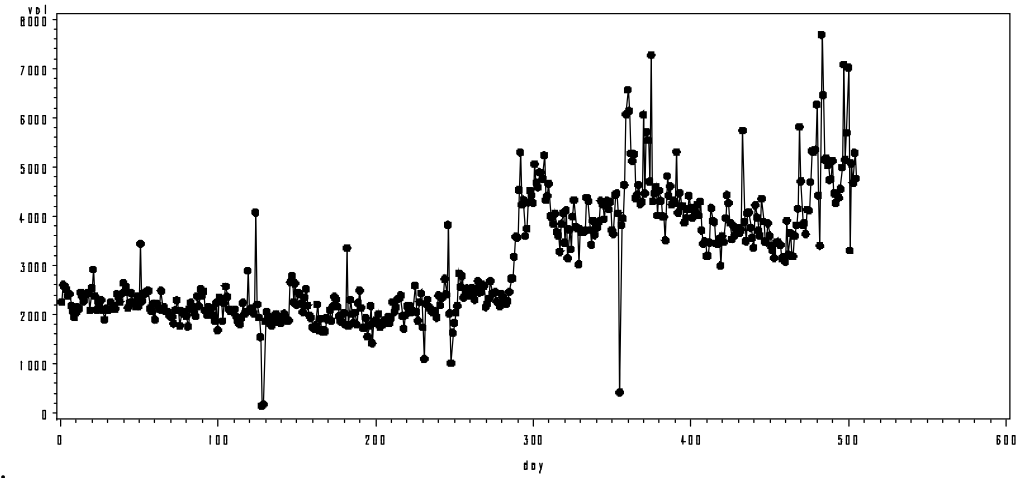

FIGURE 6. PLOT OF THE NASDAQ TRADING VOLUME OVER DAYS FOR THE PERIOD, JANUARY 1, 2019 – DECEMBER 31, 2020

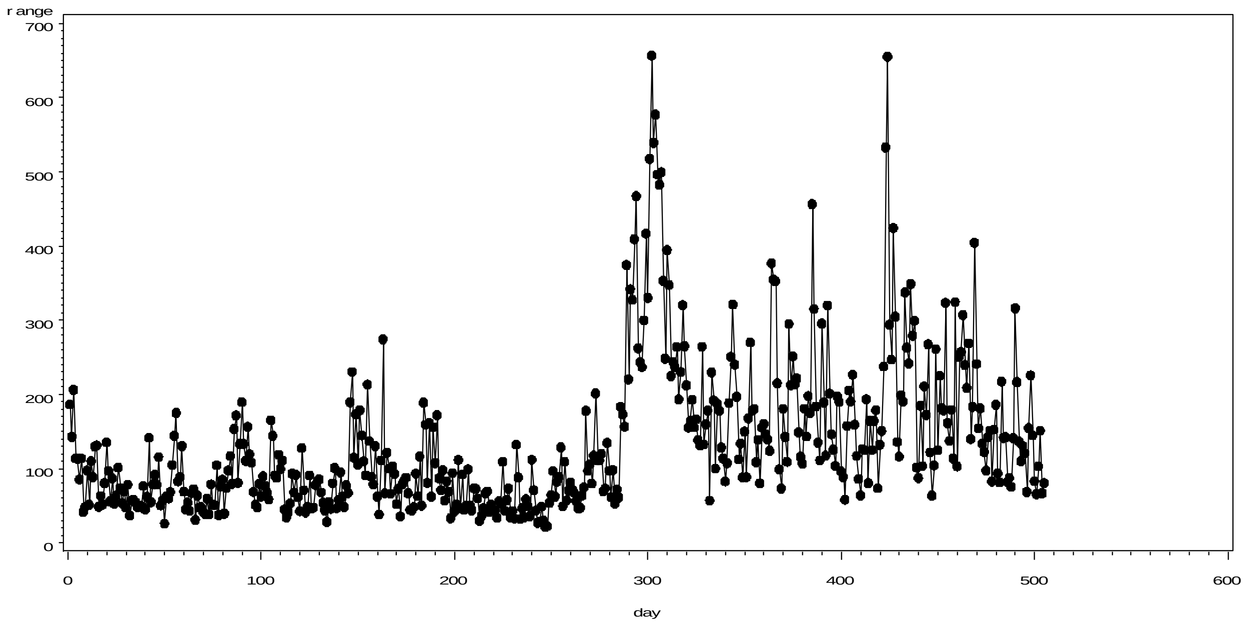

FIGURE 7. PLOT OF THE NASDAQ RANGE OVER DAYS FOR THE PERIOD, JANUARY 1, 2019 – DECEMBER 31, 2020.

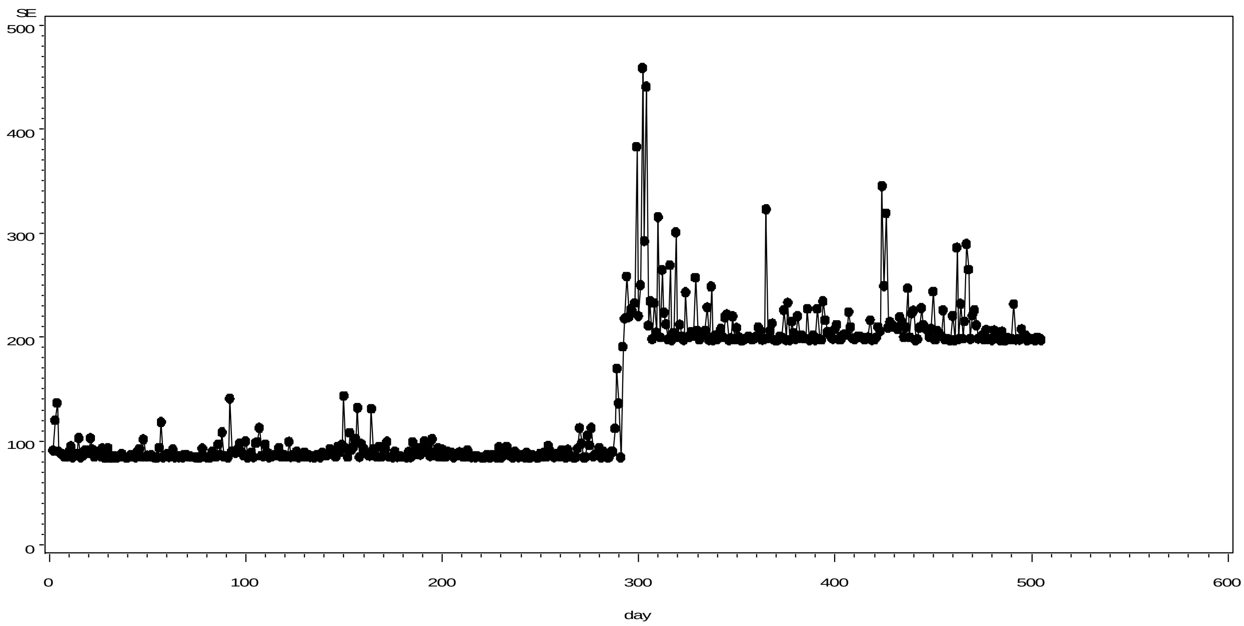

FIGURE 8. PLOT OF THE NASDAQ STANDARD ERROR OVER DAYS FOR THE PERIOD, JANUARY 1, 2019 – DECEMBER 31, 2020.

Results in Table 3 indicate that the impact of the pandemic, as seen from the w-estimates, was positive and significant for the S&P 500 returns, trading volume, SE, and range. The impact of the pandemic, as in the case of the DOW and NASDAQ, was felt 15 days after the onset of the pandemic. The graphs in Figures 9 to 12 are in agreement with the intervention analysis results in Table 3. They show a larger rate of increase, after the drop in the SP index, than is seen before the pandemic. In addition, the means of trading volume, SE, and range were larger during the pandemic as compared to the means before the pandemic.

Figures 1, 5 and 9 were similar in that they show that the DOW, NASDAQ, and S&P 500 dropped in March after which they recovered relatively fast. Table 4 shows that this drop for the period March 2, 2020 to March 20. 2020, (days 293-307) was highly significant in that the w-estimates were all negative with a p-value less than 0.0001. For this intervention, the step function in Equation (1) was taken to be 1 for the days 293 to 307 and 0 elsewhere.

TABLE 3. ESTIMATES OF THE PANDEMIC EFFECT (W), FROM THE INTERVENTION ANALYSIS MODEL IN EQUATION (3)

Variable	w estimate	Standard Error	t -value	p-value	Time-shift in days
ΔSP	8.41	3.16	2.66	0.0081	15
Volume	1309.70	195.62	6.70	<.0001	0
SE	40.84	3.18	12.84	<.0001	0
Range	30.34	8.39	3.61	0.0003	0

The symbol Δ indicates first difference for stationarity.

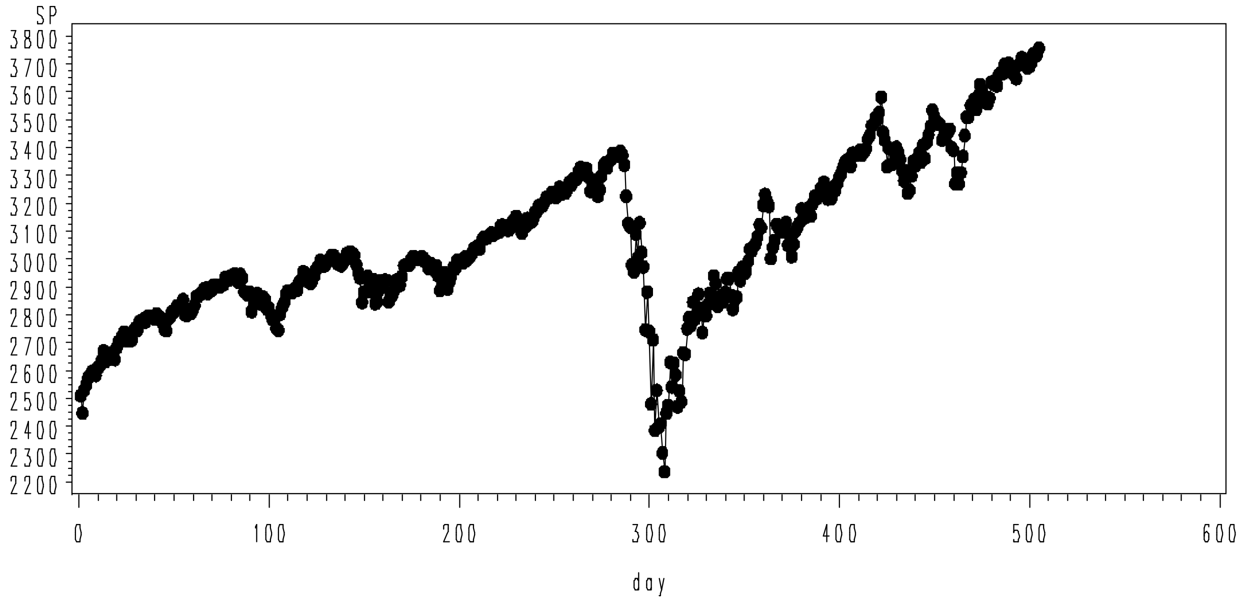

FIGURE 9. PLOT OF THE S&P 500 INDEX OVER DAYS FOR THE PERIOD, JANUARY 1, 2019 – DECEMBER 31, 2020

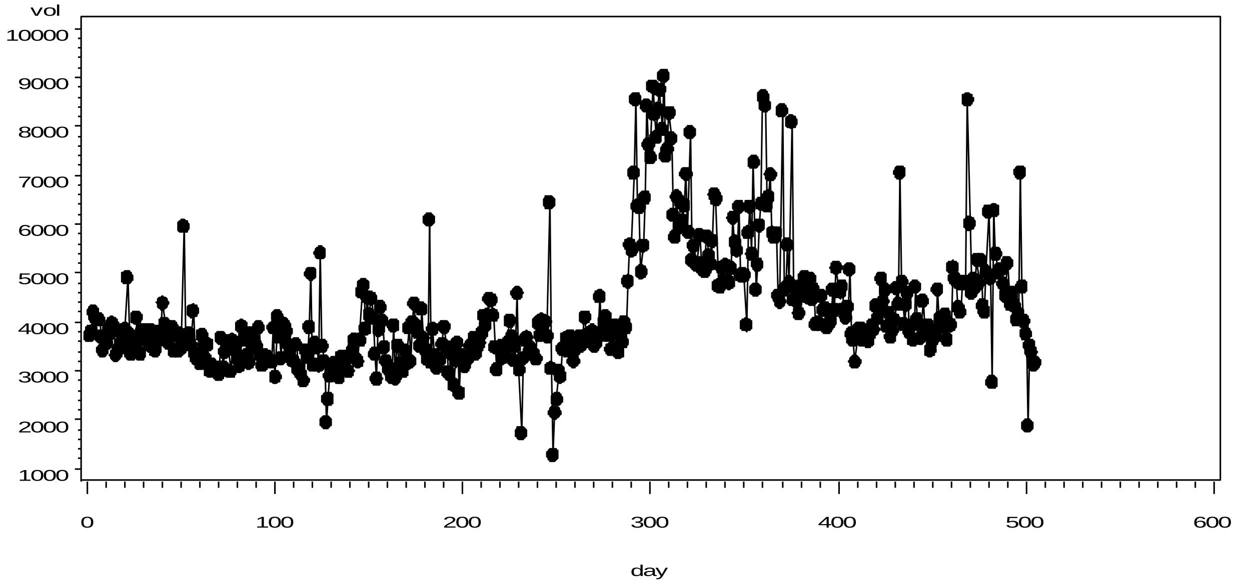

FIGURE 10. PLOT OF THE S&P 500 TRADING VOLUME OVER DAYS FOR THE PERIOD, JANUARY 1, 2019 –DECEMBER 31, 2020.

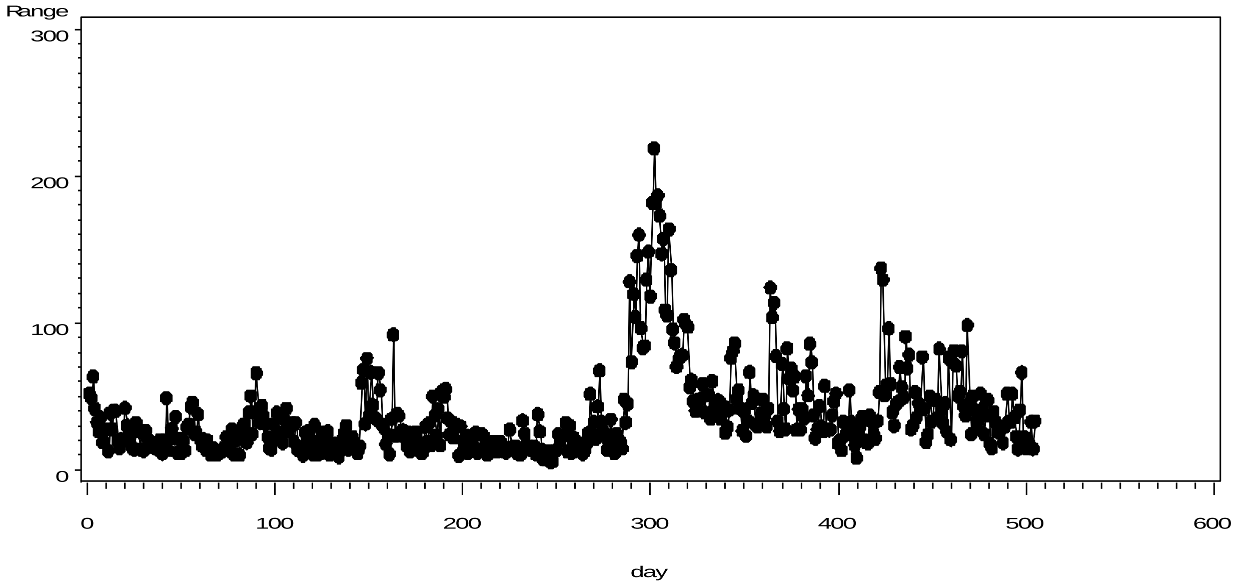

FIGURE 11. PLOT OF THE S&P 500 RANGE OVER DAYS FOR THE PERIOD, JANUARY 1, 2019 – DECEMBER 31, 2020.

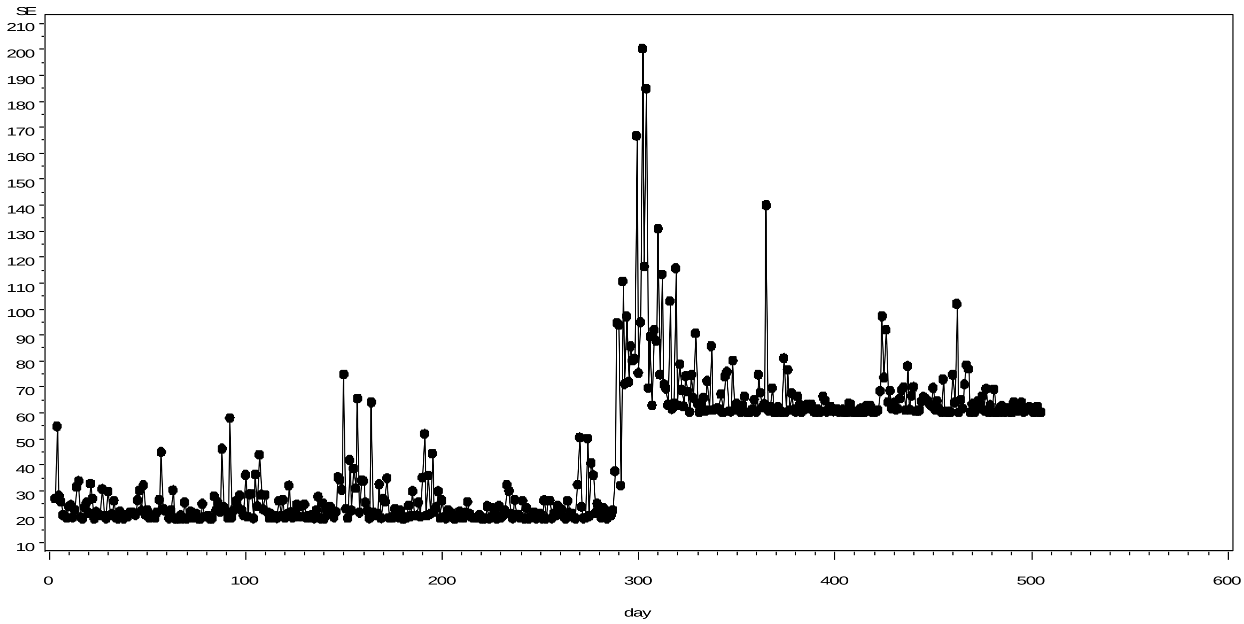

FIGURE 12. PLOT OF THE S&P 500 STANDARD ERROR OVER DAYS FOR THE PERIOD, JANUARY 1, 2019 – DECEMBER 31, 2020.

TABLE 4. ESTIMATES OF THE PANDEMIC EFFECT (W), FROM THE INTERVENTION ANALYSIS MODEL IN EQUATION (3) FOR THE PERIOD, MARCH 2, 2020 TO MARCH 20. 2020, (DAYS 293-307).

Variable	w-estimate	Standard Error	t-value	p-value
ΔDOW	-455.44	87.61	-5.20	<.0001
ΔNASDAQ	-133.55	29.25	-4.57	<.0001
ΔSP	-48.61	8.33	-5.83	<.0001

The symbol Δ indicates first difference for stationarity.

Table 5 presents results, from the model in Equation (8), on the effect of volatility (as measured by the standard error or SE) on the Dow, S&P 500, and NASDAQ daily returns as well as their daily trading volumes before and during the pandemic. As seen from the w_0 estimate in Table 5, the relationship between SE and the DOW returns was negative, but not significant, before the pandemic and changed to being positive and significant during the pandemic. The SE volatility effect on volume was positive and significant before and during the pandemic.

TABLE 5. EFFECTS OF DAILY STANDARD ERROR OF RETURNS (SE), (V(B) IN EQUATION (8) = W_0 or $W_0 - W_1B$) FOR THE PERIODS BEFORE AND DURING THE PANDEMIC

Period: January 1, 2019 to March 1, 2020					March 21, 2020 to December 31, 2020			
Variable	Estimate	Std. Error	t-value	p-value	Estimate	Std. Error	t-value	p-value
ΔDOW	$w_0 =$ - 0.353	0.514	-0.69	0.4930	$w_0 =$ 0.731 shift = 1	0.322	2.27	0.0245
Volume	$w_0 =$ 0.400	0.167	2.39	0.0177	$w_0 =$ 0.199	0.076	2.60	0.0099
ΔNASDAQ	$w_0 =$ - 0.028	.479	-0.06	0.954	$w_0 =$ -1.76	7.30	-0.24	0.809
Volume	$w_0 =$ 7.29 shift = 2 $w_1B =$ -7.26 shift =2	2.23 2.20	3.27 -3.29	0.0012 0.0011	$w_0 =$ -59.97 shift = 3 $w_1B =$ 63.21 shift = 3	32.96 32.89	-1.82 1.92	.0705 0.0562
ΔSP	$w_0 =$ -0.105	0.211	-0.50	.6182	$w_0 =$ 1.171 shift = 1	0.494	2.37	0.0189
Volume	$w_0 =$ 9.65	2.344	4.12	<.0001	$w_0 =$ 4.82	10.12	0.48	0.6345

The symbol Δ indicates first difference for stationarity

The effect of volatility on the NASDAQ returns was negative, but not significant, for both periods, before and after the pandemic. On the other hand, the effect of volatility on the NASADQ trading volume was positive before the pandemic and negative during the pandemic.

The effect of volatility on the S&P 500 returns was negative, but not significant, before the pandemic and changed to being significantly positive during the pandemic. The effect of volatility on the daily trading volume was positive and significant before the pandemic and positive, but not significant, during the pandemic. Clearly, there was an effect of the pandemic with regard to the relationships between volatility and the DOW returns, the NASDAQ trading volume, S&P 500 returns, and its trading volume.

Table 6 presents the relationships between volatility, as measured by the daily range, and the daily returns on the DOW, S&P 500, and NASDAQ indexes and their trading volumes for the periods before and during the pandemic. It is seen from Table 6 that the relationship between volatility and the DOW returns was negative before the onset of the pandemic and positive during the pandemic. There was no change in the positive relationship between volatility and the trading volume as a result of the pandemic.

The effect of volatility on the NASADQ returns was negative for both periods. Also, the effect on volume was positive for both periods. The relationship between volatility and the returns on the S&P 500 was negative for both periods but became insignificant during the pandemic. The relationship of volatility on the SP trading volume was positive for both periods.

There is some evidence in the literature of a negative relationship between market returns and volatility in the case of the S&P 500 (Crestmont Research, 2011). This is seen to be the case, in this analysis, for the DOW, S&P 500, and NASDAQ before the pandemic. This relationship changed for the DOW and the S&P 500 as a result of the pandemic.

TABLE 6. EFFECTS OF DAILY RANGE (V(B) IN EQUATION (8) = W_0 or $W_0 – W_1B$) FOR THE PERIODS BEFORE AND DURING THE PANDEMIC

Period: January 1, 2019 to March 1,2020					March 21, 2020 to December 31, 2020			
Variable	Estimate	Std. Error	t-value	p-value	Estimate	Std. Error	t-value	p-value
ΔDOW	w_0 = -0.651	0.082	-7.91	<.0001	w_0 = 0.340 shift = 1	0.123	2.76	0.0063
Volume	w_0 = 0.244	0.029	8.39	<.0001	w_0 = 0.336	0.0232	14.46	<.0001
ΔNASDAQ	w_0 = -0.588	0.090	-6.51	<.0001	w_0 = -0.589	0.106	-5.51	<.0001
Volume	w_0 = 3.485	0.468	7.43	<.0001	w_0 = 2.304	0.588	3.91	0.0001
ΔSP	w_0 = -0.649	0.080	-8.03	<.0001	w_0 = -0.093	0.111	-0.83	0.4049
Volume	w_0 = 18.95	2.22	8.55	<.0001	w_0 = 17.35	2.54	6.82	<.0001

The symbol Δ indicates first difference for stationarity.

CONCLUSION

This study investigated the effect of the COVID-19 pandemic on the daily returns, trading volume, and volatility with regard to the DOW, S&P 500, and NASDAQ on the US stock market.

In addition, the study examined the effect of the pandemic on the relationships between volatility and returns as well as volatility and trading volume. The time series analysis used was the intervention analysis, the transfer function time series regression approach, and the autoregressive conditional heteroscedasticity (ARCH) model. Volatility was measured by the daily range (high - low) of an index and by the daily standard error of returns from the ARCH (!) model.

Results from the intervention analysis showed a significant positive impact of the pandemic on trading volume, and volatility for the three indexes. Also, the onset of the pandemic caused first a steep drop in returns for the three indexes, which was followed by an increase in returns as compared to the period before the pandemic. Furthermore, the pandemic affected the relationships that existed between volatility and returns in the case of the DOW and S&P 500. Also, it had an effect on the relationship between volatility and volume for the NASDAQ and S&P 500.

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