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Stand Still and Do Nothing: COVID-19 and Stock Returns and Volatility

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ABSTRACT

We examine the intraday returns and volatility in the US equity market amid the COVID-19 pandemic crisis. Our empirical results suggest an increase in volatility over time with mostly negative returns and higher volatility in the last trading session of the day. Our Univariate analysis reveals structural break(s) since the first trading halt in March 2020 and that failure to account for this may lead to biased and unstable conditional estimates. Allowing for time-varying conditional variance and conditional correlation, our dynamic conditional correlation tests suggest that COVID-19 cases and deaths are jointly related to stock returns and realised volatility.
Key words: COVID-19, Stock Returns and Volatility, DCC, Multivariate GARCH.

1. INTRODUCTION

Financial markets have experienced unprecedented levels of volatility in March 2020 since the outbreak of the COVID-19 global pandemic. The extent of the panic can be gauged from the US equity market where trading was halted on the New York Stock Exchange (NYSE) on the 9th, 12th, 16th, and 18th of March as the S&P500 dropped[1]. The VIX volatility index increased from 17.08 on February 21 to 82.70 on March 16 after the World Health Organisation (WHO) declared COVID-19 a global pandemic on March 11, 2020[2]. Stock prices fell 30% compared to the 34% drop of the 1987 market crash (Siegel, 2020). It has led to the end of the record 11 years longest bull market in mid-March[3]. In May and June, the VIX volatility index is on average double the level it was in

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[1] https://graphics.reuters.com/USA-MARKETS/0100B5L144C/index.html
[2] https://www.who.int/emergencies/diseases/novel-coronavirus-2019/events-as-they-happen
[3] https://crsreports.congress.gov/product/pdf/IN/IN11309

January 2020[4]. Such high levels of volatility may only favour volatility traders particularly in the options markets; however, it is detrimental for risk-averse investors (Chance and Brooks). It must be noted that it is the first time that such a crisis in financial markets in peacetime is induced by a simultaneous disruption to both supply and demand (Siegel, 2020).

The emerging literature on the COVID-19 pandemic and its implications for financial markets is still at an early stage. These studies have focused mostly on volatility and the aspects of the COVID-19 pandemic such as new cases, the number of daily deaths, sentiments, media coverage, etc. (Baig et al., 2020; Haroon and Rizvi, 2020; Onali, 2020; Papadamou et al., 2020; Baker et al., 2020). Most of these studies have provided empirical evidence in support of the impact of the COVID-19 crisis (cases and deaths) on stock returns and volatility (Baig et. Al., 2020; Haroon and Rizvi, 2020; Mirza et al., 2020; Yousaf, 2020; Zhang et al, 2020). However, these studies have mainly analysed daily data on returns; have a relatively shorter sample period post the peak of the market volatility in March 2020.

Volatility has broad implications for trading, asset pricing, investment, and risk management. COVID-19 pandemic-induced volatility leads to a shift of informed trading activity to dark pools from lit avenues (Ibikunle and Rzayev, 2020). This has significant implications for asset pricing particularly in terms of price discovery due to loss of informational efficiency (Ibikunle and Rzayev, 2020). The conditional correlation between stock returns of both financial and non-financial firms across countries increased during the COVID-19 pandemic period that implies financial contagion leading to higher optimal hedge ratios and hence higher hedging costs (Akhtaruzzaman et al., 2020). The use of daily stock price data to measure stock returns and volatility may not be appropriate particularly given high-frequency trading (HFT) based on algorithms that closely monitor changes in stock prices and the resulting consequences for market liquidity (Anagnostidis and Fontaine, 2020). The intra-day trend and patterns in both stock returns and volatility have significant implications for market timing and trading

[4] http://www.cboe.com/vix

activities. This is particularly significant given the circuit breaker rules in place on the NYSE where trading halt do not apply after 3:25 p.m. if the S&P500 drops below 7%[5].

In this study, first, we analyse the intraday day i.e. 10 minutes S&P500 index data accounting for the evolution of the realised volatility and its trends and patterns during different trading hours over each trading day. Then we investigate the volatility in the market using the intraday returns using univariate GARCH models. However, unlike the extant literature we use the log-likelihood ratio to choose different GARCH specifications for before and after the first trading halt (i.e. 9th March 2020) as well as the full sample period i.e. 2nd January to 5th June 2020. We do not use Exponential GARCH given stationarity of the time series of intraday returns[6]. Finally, we analyse the relationship between stock returns and volatility with COVID-19 cases and deaths using the Dynamic Conditional Correlation (DCC) multivariate GARCH. Unlike the conventional multivariate GARCH, the DCC multivariate GARCH directly parameterise conditional correlations. Another advantage is that the number of series considered in the analysis has no role in the determination of the number of parameters estimated (Engle, 2002).

2. DATA AND EMPIRICAL METHODS

For our empirical analysis and evaluation, we have used the S&P500 index as a benchmark proxy of US equity prices. Our sample covers the intraday S&P500 index values at the 10-minute interval from 2nd January to 5th June 2020 obtained from Bloomberg. Data on confirmed COVID-19 total cases, new cases, total death, and new death in the US is obtained from Oxford COVID-19 Government Response Tracker (OxCGRT)[7].

We calculate the logarithmic 10 minutes return (r_{t10}) as:

$$r_{t10} = \ln\left(\frac{P_{t10}}{P_{t10-1}}\right) * 100 \qquad (1)$$

[5] https://www.nyse.com/markets/hours-calendars

[6] Different specifications, including ARFIMA, were considered in each case and selection was based in each case on the Log-likelihood ratio.

[7] https://www.bsg.ox.ac.uk/research/research-projects/coronavirus-government-response-tracker#data

Where $P_{t10}$the current 10-minute is the value of the S&P500 index and $P_{t10-1}$is the lagged 10-minute value of the S&P500 index. We calculate the realised volatility for any trading day (RV_D) as the sum of the squared r_{t10} (i.e. $RV_D = \sum_{i=1}^{N} r_{t10}^2$) for each day. We then divided the trading day into four equal 2 hours' sessions and calculate the realised volatility for each session similarly to ascertain the pattern and trends in realised volatility and returns over the day.

First, we use standard univariate GARCH to analyse the conditional volatility of the intraday returns and assess different specifications in both mean and variance equations to choose the best fit based on the log-likelihood ratio. The conditional mean and variance equations in the standard GARCH model are given in equation 2 and 3 as:

$$r_{t10} = \mu + ar(1) + ar(2) + \cdots ar(n) + ma(1) + ma(2) + \cdots + ma(n) + \varepsilon_{t10} \tag{2}$$

$$h_{t10} = \omega + \sum_{i=1}^{q} a_i\, \varepsilon_{t10-i}^2 + \sum_{j=1}^{p} \beta_j\, h_{t10-j} \tag{3}$$

Where μ is the intercept term, $ar(.)$ and $ma(.)$are the autoregressive and moving average components of the conditional mean equation and ε_{t10} is a residual term of the mean equation. Further, h_{t10} is the conditional variance of r_{t10}, ω is the alpha (intercept) term while q and p represent the lag order of the squared residual term (ε_{t10}^2) and the conditional variance (h_{t10}) with a_i and β_j estimated coefficients respectively in the conditional variance equation. We selected the best fit from our estimations of the specifications (in mean and variance) of the standard GARCH for the full sample as well as before and after 9th March 2020 subsample periods based on the log-likelihood criterion[8].

We use the DCC, multivariate GARCH approach to measure the impact of the COVID-19 pandemic crisis on stock returns and volatility. It is a two steps process; the first step is a series of univariate GARCH estimates and the second step involves

[8] We divided the sample based on the first trading halt on the opening of trading on the 9th of March 2020. So we have the first period before the first trading halt from 2nd January to 6th March 2020 and then from 9th March to 5th June 2020 that includes the extreme volatility from 9th March to the last week of trading in March.

conditional correlation estimates (Engle, 2002). The conditional correlation (ρ_t) between two random variables (returns on two assets) r_1 and r_2 is[9]:

$$\rho_{r_1 r_2,t} = \frac{E_{t-1}(r_{1,t} r_{2,t})}{\sqrt{E_{t-1}(r^2_{1,t)}) + E_{t-1}(r^2_{2,t)})}} \qquad (4)$$

The conditional returns on any are then equal to:

$$r_{i,t} = \sqrt{h_{i,t} \varepsilon_{i,t}} \text{, where } h_{i,t} = E_{t-1}(r^2_{i,t)}$$

Given that, $\varepsilon_{i,t}$ i.e. the standardised disturbance has zero mean and constant variance of one for each series, the conditional variance in equation 4 can be shown to equal the conditional covariance between the standardised disturbances of the two series. Mathematically, this is:

$$\rho_{r_1 r_2,t} = \frac{E_{t-1}(\varepsilon_{1,t} \varepsilon_{2,t})}{\sqrt{E_{t-1}(\varepsilon^2_{1,t)}) + E_{t-1}(\varepsilon^2_{2,t)})}} = E_{t-1}(\varepsilon_{1,t} \varepsilon_{2,t}) \qquad (5)$$

The empirical rolling correlation estimator for series of returns with zero means is:

$$\hat{\rho}_{r_1 r_2,t} = \frac{\sum_{s=t-n-1}^{t-1} r_{1,s} r_{2,s}}{\sqrt{(\sum_{s=t-n-1}^{t-1} r^2_{1,s}) + (\sum_{s=t-n-1}^{t-1} r^2_{2,s})}} \qquad (6)$$

However, the limitation of the conditional correlation estimator in equation 6 is that it ignores all older observations and gives equal weight to those less than n periods. Use of declining weights based on a given parameter λ that gives more weight to current values, however, has no fixed termination point i.e. an exponential smoother overcomes this problem. Mathematically the conditional correlation with exponential smoother is:

$$\hat{\rho}_{r_1 r_2,t} = \frac{\sum_{s=1}^{t-1} \lambda^{t-j-1} r_{1,s} r_{2,s}}{\sqrt{(\sum_{s=1}^{t-1} \lambda^{t-j-1} r^2_{1,s}) + (\sum_{s=1}^{t-1} \lambda^{t-j-1} r^2_{2,s})}} \qquad (7)$$

Next, we provide the results and discussions of our empirical analysis and estimation.

[9] The DCC multivariate GARCH approach described here is from Engle (2002).

3. EMPIRICAL RESULTS

Table 1 presents the descriptive statistics on the 10-minute intraday returns for January through May 2020 and the full sample period. The returns are negative in the first three months and then positive for April and June. The volatility as measured by standard deviation is rising from January to March (0.278% to 0.984%) and then falling onward (0.382% in May). Figure 1 depicts the S&P500 daily average 10-minute returns and the square root of the cumulative squared 10-minute returns as the measure of volatility. Overall, this trend in returns and volatility coincides with the progression of the COVID1-9 pandemic crisis. The relative stability after March 2020 is partially due to the US government policy responses to stabilise the economy and Federal Reserve measures for financial stability.

Table 1

Descriptive Statistics on Intraday Returns

	Mean	Std.Dev	Min	Max
Jan-20	-0.002	0.278	-1.622	1.623
Feb-20	-0.012	0.357	-1.791	2.581
Mar-20	-0.017	0.984	-8.936	8.028
Apr-20	0.015	0.562	-2.541	5.488
May-20	0.006	0.382	-1.754	4.066
Full Sample	0.000	0.574	-8.936	8.028

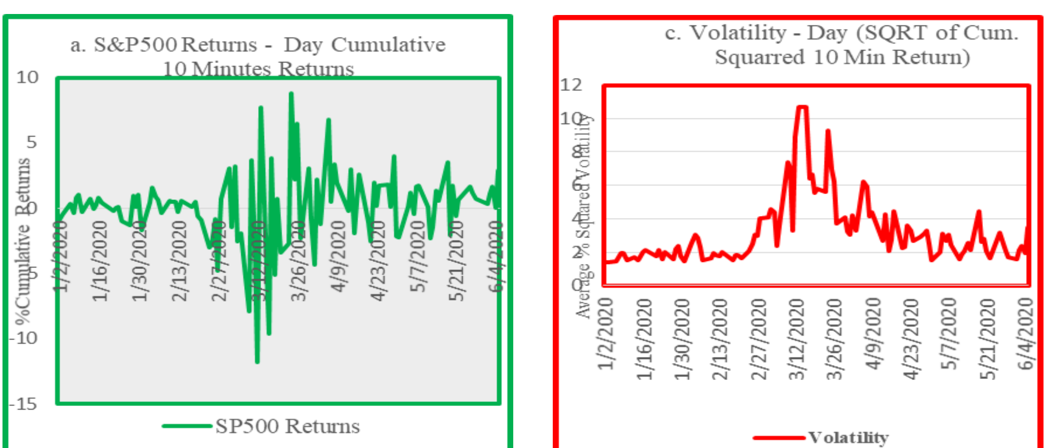
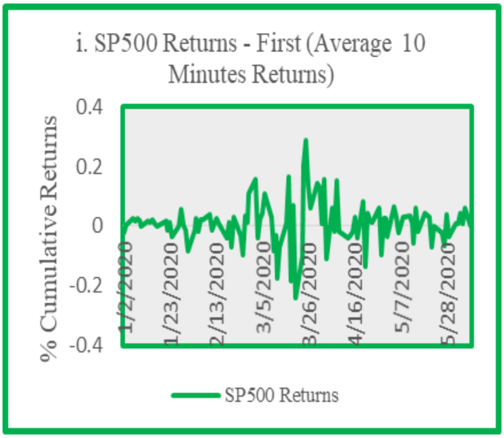
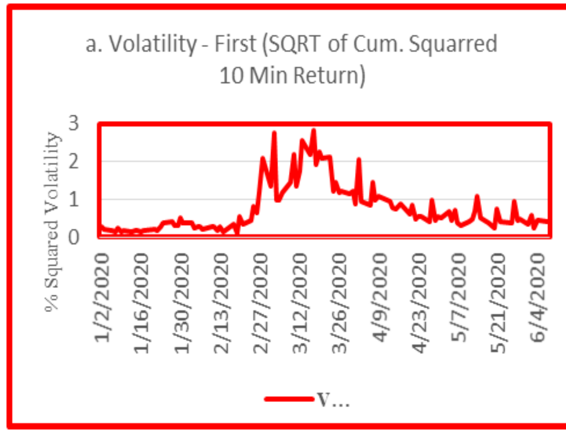
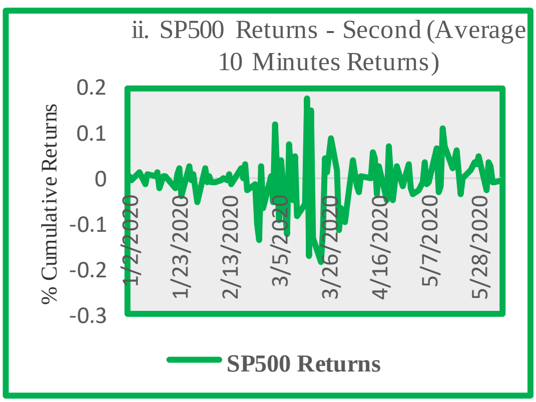
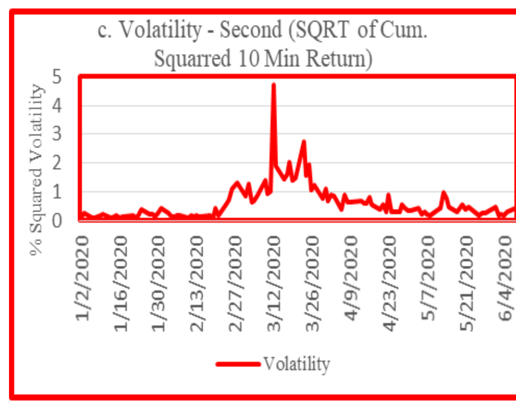


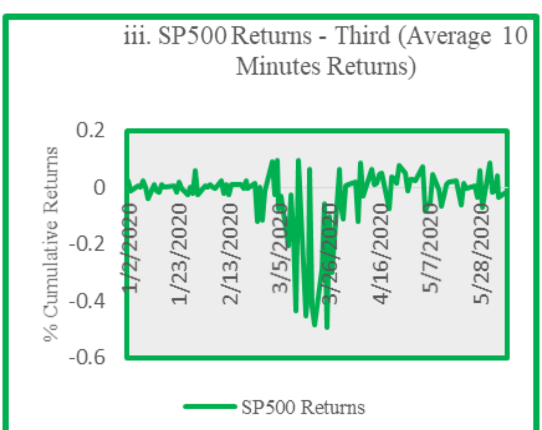
Figure. 1. S&P500 Cumulative Daily Returns and Volatility

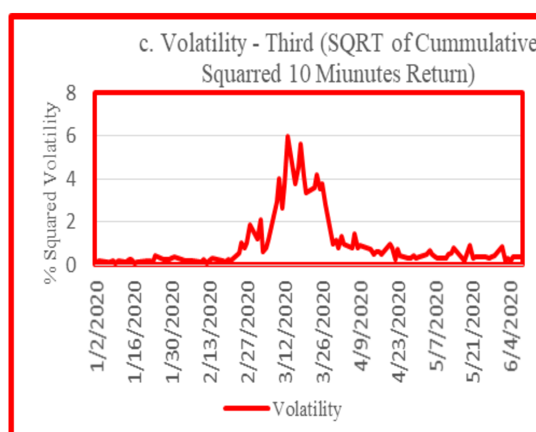

i. SP500 Returns - First (Average 10 Minutes Returns)
% Cumulative Returns
0.4
0.2
0
-0.2
-0.4
1/2/2020
1/23/2020
2/13/2020
3/5/2020
3/26/2020
4/16/2020
5/7/2020
5/28/2020
SP500 Returns


a. Volatility - First (SQRT of Cum. Squarred 10 Min Return)
% Squared Volatility
3
2
1
0
1/2/2020
1/16/2020
1/30/2020
2/13/2020
2/27/2020
3/12/2020
3/26/2020
4/9/2020
4/23/2020
5/7/2020
5/21/2020
6/4/2020
V...


ii. SP500 Returns - Second (Average 10 Minutes Returns)
% Cumulative Returns
0.2
0.1
0
-0.1
-0.2
-0.3
1/2/2020
1/23/2020
2/13/2020
3/5/2020
3/26/2020
4/16/2020
5/7/2020
5/28/2020
SP500 Returns


c. Volatility - Second (SQRT of Cum. Squarred 10 Min Return)
% Squared Volatility
5
4
3
2
1
0
1/2/2020
1/16/2020
1/30/2020
2/13/2020
2/27/2020
3/12/2020
3/26/2020
4/9/2020
4/23/2020
5/7/2020
5/21/2020
6/4/2020
Volatility


iii. SP500 Returns - Third (Average 10 Minutes Returns)
% Cumulative Returns
0.2
0
-0.2
-0.4
-0.6
1/2/2020
1/23/2020
2/13/2020
3/5/2020
3/26/2020
4/16/2020
5/7/2020
5/28/2020
SP500 Returns


c. Volatility - Third (SQRT of Cummulative Squarred 10 Miunutes Return)
% Squared Volatility
8
6
4
2
0
1/2/2020
1/16/2020
1/30/2020
2/13/2020
2/27/2020
3/12/2020
3/26/2020
4/9/2020
4/23/2020
5/7/2020
5/21/2020
6/4/2020
Volatility

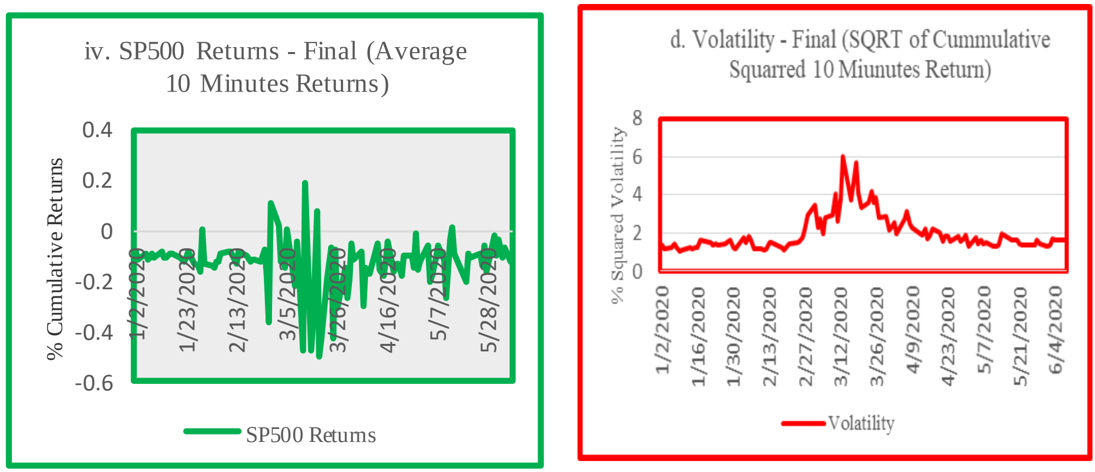


Figure 2. S&P500 Intraday Returns Volatility in Sessions Overtime

Figure 2 presents the S&P500 average 10-minute returns and volatility for the first, second, third, and final session of the trading day. The returns and volatility in the last session depict relatively different levels than the first three sessions. The average returns are mostly negative and volatility is mostly twice of other sessions before and after the March crisis. The circuit breakers in the market are not effective after 3:25 p.m. as well as closing positions are taken in early sessions may explain the observed pattern[10].

The Augmented Dickey-Fuller (ADF) test results reported in Table 2 suggest that the time series of S&P500 returns has no unit and are stationary; however, there are ARCH effects as suggested by the Box-Ljung test statistic that is statistically significant at 1%. Therefore, we use standard GARCH specifications in our univariate analysis.

Table 2			
Diagnostic Tests			
Augmented Dickey-Fuller Test			
Lag	None	Drift	Drift & Trend
0	-69.100	-69.100	-69.100
1	-50.600	-50.600	-50.600
2	-48.400	-48.400	-48.500

[10] https://www.investopedia.com/articles/investing/050313/activities-you-can-take-advantage-premarket-and-afterhours-trading-sessions.asp

3	-40.400	-40.400	-40.400
4	-35.900	-35.900	-36.000
ARCH Effects			
	X -Squarred	df	p-value
Box-Ljung test	168.55	12	0.000

Table 3 presents the estimates (with and without robust standard errors) for GARCH (2, 2), ARMA(1, 1) specification selected based on log-likelihood ratio. The sum of α and β terms is less than 1 i.e. (α + β <1) suggesting that our GARCH specification is stable. In addition, the sign bias tests reported in Table 2 suggest no misspecification of the model. However, the Nyblom joint parameter stability test is statistically significant at one percent and suggests that at least one of the parameter is not constant over time and hence suggest structural change(s) in the relationship overtime.

Table 3								
Univariate GARCH (2,2), ARMA(1,1)								
	μ	ar(1)	ma(1)	ω	α_1	α_2	β_1	β_2
Coefficient	-0.001	0.749	-0.867	0.001	0.033	0.000	0.014	0.950
S.E	0.003	0.024	0.017	0.000	0.003	0.003	0.001	0.000
t-Value	-0.310	31.853	-51.406	6.058	12.717	0.000	10.331	2387.686
p-Value	0.756	0.000	0.000	0.000	0.000	1.000	0.000	0.000
Coefficient	-0.001	0.749	-0.867	0.001	0.033	0.000	0.015	0.950
Robust S.E	0.003	0.017	0.014	0.000	0.009	0.012	0.001	0.003
t-Value	-0.283	44.039	-64.008	2.313	3.670	0.000	11.993	369.553
p-Value	0.777	0.000	0.000	0.021	0.000	1.000	0.000	0.000
Nyblom Stability Test								
Individual	0.3948	0.1476	0.2231	0.103	0.1166	0.9031	0.1002	0.1045
Joint	23.701							
Nyblom Asymp. C. Values					Sign Bias Test			
	10%	5%	1%				*t*-Stat.	*p*-Value
Joint Stat.	1.890	2.110	2.590		Sign Bias		0.487	0.626
Individual Stat.	0.350	0.470	0.750		Negative		0.148	0.882
					Positive		1.102	0.271
Log-Likelihood	-2911.05				Joint		1.971	0.579

To analyse this further, we estimate different GARCH models dividing the sample into before and after every trading halt in March 2020 i.e. March 9, 12, 16, and 18. The Nyblom joint parameter stability tests before and after each trading halt are presented in Table 4. It suggests that there is a structural change in the volatility of S&P500 returns after March 9 as the Nyblom joint parameter tests are statistically significant at five percent in all cases that incorporate intraday data from March 9 to March 16, 2020. It is an important observation as it suggests that GARCH specifications used in the empirical investigation should explicitly account for this structural break. If not accounted for, the estimates of conditional volatility may be systematically biased. This structural break coincides with the intensity of the COVID-19 pandemic that peaked in the second week of March 2020 as the WHO officially declared it as a global pandemic. After which, US government announced travel restrictions, social distancing rules and other measures related to lockdown.

Table 4

Nyblom Stability Joint Test Results Subsamples

	GARCH (1,1), ARMA(0,0)	GARCH(2,2), ARMA(3,2)
	Before	After
9th March 2020	0.748	14.604***
Log-likelihood	-2249.749	-1751.550
	GARCH(1,1), ARMA(3,2)	GARCH(1,1), ARMA(3,2)
12th March 2020	4.161***	13.573***
Log-likelihood	-860.757	-1542.288
	GARCH(1,1), ARMA(3,2)	GARCH(1,1), ARMA(3,2)
16th March 2020	2.773**	1.936
Log-likelihood	-1031.451	-1692.516
	GARCH(1,1), ARMA(3,2)	GARCH(1,1), ARMA(3,2)
18th March 2020	8.767***	1.572
Log-likelihood	-938.938	-1574.992

Subsequently, we provide the DCC multivariate GARCH estimates in Table 5. As the DCC multivariate GARCH allows both conditional variance and conditional correlation to vary over time and is recursive, therefore, it is robust against structural breaks (Orskaug, 2009). We employ a copula-based multivariate GARCH model that allows estimation without explicit regulatory conditions. The model assumes a standard Gaussian copula and parameters are optimized using maximum likelihood. The models with S&P 500 returns and realized volatility are of ARMA (0, 0), GARCH (1, 1), and DCC (1, 1) order[11.]

The variable dcca1 represents the joint correlation of the variables in the system. Under the null, the dynamic conditional correlation is jointly zero for all the variables. Our results in Table 5 show that the dynamic conditional correlation of COVID-19 total cases, new cases, total deaths and new deaths with both S&P500 returns and realized volatility are not equal to zero[12]. The variable dccb1 tests the null the conditional correlation over time is equal to 1. Based on our results in Table 5, we reject the null and confirm that the correlation remains less than 1. The multivariate model results confirm that the dynamic conditional correlation of COVID-19 variables with realized volatility and S&P 500 returns is significant and positive over the period of study consistent with the notion of 'the higher the risk, the higher the return'[13]. Our results provide robust empirical evidence to the otherwise intuitive understanding that uncertainty caused by COVID has indeed caused higher realized volatility in S&P 500 returns.

Table 5

DCC Multivariate GARCH Estimates

S&P500 Returns					S&P500 Realised Volatility			
		Coeff.	Prob.				Coeff.	Prob.
Joint	dcca1	0.109	0.063		Joint	dcca1	0.100	0.000
	dccb2	0.875	0.000			dccb2	0.869	0.000

[11] The ARMA order is chosen based on the combined model convergence. Since the initial number of new cases and new deaths are zero in our sample, therefore, there was no evidence of volatility. Based on this shortcoming the multivariate model showed no convergence. However, after testing the model with multiple variations, we chose multivariate model with ARMA (0, 0)

[12] We find similar results when the DCC multivariate GARCH models are estimated separately with total cases & deaths and new cases and deaths.

[13] The S&P500 was at 3386.15 on February 19 2020 and was at 3232.39 on June 8 2020.

4. CONCLUSION

In this paper, we analyse the patterns and trends in the intraday stock returns and volatility in the US equity market amid the global COVID-19 pandemic. We use the intraday 10-minute S&P500 index values as a proxy for stock prices in the US equity market. Our descriptive analysis reveals that both returns and volatility exhibit different patterns over the sample period in line and coinciding with the COVID-19 pandemic. Average returns are negative (positive) and volatility is rising (falling) from January to March 2020 (March to May 2020). Intraday day patterns in returns and volatility suggest that the returns are mostly negatively and highly volatile in the last trading sessions relative to earlier sessions in the day.

The findings from our univariate GARCH analysis and Nyblom parameters stability test suggest structural break(s) in data in March 2020 after the first trading halt took place on 9th March 2020. We find that different univariate GARCH specification fits in each case for before and after the trading halt trading periods. Duly we employ dynamic conditional correlation (DCC) multivariate GARCH to assess the relationship of stock returns and volatility with the number of total and new cases as well as total deaths and new deaths. Our empirical results confirm that COVID-19 cases and deaths (total and new) have a statistically significant dynamic conditional correlation with stock returns and volatility. Over time, we observe that the market has recovered from the panic in March 2020 and a strategy of standing still and doing nothing would have enabled investors to save on trading costs and taxes.

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