 doi:10.20944/preprints202203.0281.v1

Impact of COVID-19 on Local Markets: An Application of GARCH and Markov-Switching Dynamic Regression

Capstone Project

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March 21, 2022

Abstract

COVID-19, a global health crisis, occurred unexpectedly and has led to global transformation over all countries in the world today. While COVID-19 had claimed lives and led to an economic crisis, the impacts on the financial market cannot be overemphasized. Considering the previous financial crisis, which occurred due to poor regulations and unchecked misconduct by financial market stakeholders, COVID-19 is the first to mention an indirect crisis that almost has no direct relationship to the financial system. Thus, this paper explores the impacts of COVID-19 from a stochastic approach on Local markets by applying the GARCH model to measure the level of volatility of two (2) US stock indexes (NASDAQ and NYSE) and a Europe index (EURONEXT). Our results show that volatility existed before COVID-19, but the volatility rate increased after COVID-19, possibly due to the COVID-19 shock. We also explore the Markov-Switching Dynamic Regression (MSDR) model to corroborate our findings. We validated that there is a very high persistent volatility for all the considered local markets at the early stage COVID-19 period.

Keywords COVID-19 · GARCH · ARCH · MSDR · VOLATILITY

1 Introduction

The coronavirus disease has brought unprecedented unrest to the world financial economy. According to the report released by China Daily, in March 2020, the US financial economy has suffered a more significant decline than during the Black Monday crisis in October 1987. COVID-19 has brought about unexpected shocks in the financial market and different panics regarding investment on stock market indices. During this time, the US government triggered the market circuit breaker four times to recover from the financial crisis. Investors must understand the rate at which stock prices alternate during and after the COVID-19 to aid their investment decision. Volatility is so fragile that it predominantly affects the stock market unexpectedly. However, not having accurate information regarding volatility might make investors invest in the wrong market even though it looks promising. Therefore, a proper understanding of the volatility level will help make decisive decisions related to stocks.
For this study, we will be considering two local stock markets in the United States (NASDAQ and NYSE) and one in Europe (EURONEXT) as a case study. This paper will focus on conducting an extensive analysis to understand the state of the market six months before COVID-19 (June 2019 - January 2020) and compare that to the effect of COVID-19 on the selected stock markets during the lockdown period (January 2020 - July 2020) and after post lockdown period (August 2020 through December 2020).
Also, we were able to effectively fit a Markov-Switching Dynamic Regression (MSDR) Model to various stock data in the United States and Europe in this work. This helps us calculate the means of the two regime states, the probability of migrating from one regime to the other, and the volatility experienced over this time using the MSDR. This technique enables us to track changes in stock dynamics in the United States and Europe before and after the COVID-19 epidemic.

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2 Literature Review

The COVID-19 Pandemic presents a global public health crisis with no stipulated termination date. This is a result of the evolution of the genetic composition of COVID-19 to new variants such as COVID-19 Omicron variants reported by WHO on November 28, 2021. The Omicron variant is becoming rampant and deadly, leading to countries imposing restrictions on affected countries. Aside from its high fatality rate, COVID-19 poses a significant challenge to the financial markets because it is neither an economic nor financial crisis.
The economic and financial crises experienced in the past have led to innovative approaches to mitigate any potential financial crisis before it becomes as big as the Global Financial Crisis. However, COVID-19 doesn't directly affect the financial market, as highlighted by [1]. It involves the health of millions of people, which ultimately affects the demand and supply market conditions. The cumulative effect of the demand and supply leads to unproductivity and economic crisis. According to [2], the US had its unemployment rate increase from 3.5% in February 2020 to 14.7% in April 2020 during the lockdown, thus creating a drop in the annual GDP expected for 2020. Also,COVID-19 led to brief financial stresses in the US Market,which saw the S&P 500 index lose one-third of its value from February 2020 to March 2020 and only gain back its value in August 2020. The US had a fast recovery from the potential financial crisis perceived from the pandemic development due to the role played by the Federal Reserve and Congress. The Federal Reserve and Congressmen explore the policy used during the Global Financial crisis to revert back to the pre-COVID era. Thus, the role played by the US in response to the Pandemic has been of great interest to researchers.
Since the Inception of COVID-19, several authors have come up with several approaches regarding measuring the effect [3] or the rate at which volatility has affected local financial markets in the world. [4] applied wavelet bases quantile to an algorithm to measure the effect to which volatility has affected the financial economy of China and the United States. Their approach shows that the stock market demonstrates a significant leverage effect in both the United States and China. However, they discovered that there was a high and negative impact on the United States stock market at the early stage of the COVID-19.
Wang[5] also applied a Generalized Autoregressive Conditional Heteroscedasticity (GARCH) approach to measure the effect of COVID-19 on some Chinese financial markets. Based on their research, they found out that there was a positive influence of the shock on pharmaceutical and telecommunications industries while there is a significant negative effect on other industries such as accommodation, financial services, and catering. However, [6] discovered that the level of volatility in the Romanian stock market during the early stage of COVID-19 is very close to the level of volatility that happened during the global financial crises that happened in 2007-2009. In addition, a study by [7] proves that the Indian stock market experience high volatility during the COVID period. Their major approach to achieving this was to compare the effect of the volatility before COVID- 19 and during COVID-19. In addition, the GARCH model has been found to be very effective when it comes to financial data, such as symmetric volatility or volatility clustering. However, the traditional portfolio method assumes that there is a normal and Identical distribution in the logarithm of stock prices [8] and [9].
Following the claims by the researchers above, we will be considering adopting the use of GARCH in order to confirm some of the claims that were raised that were made by the previous researchers. However, we believe that by adopting a Markov-Switching Autoregressive Modelling approach, we will be able to provide more insight into the reason and extent to which the volatility has reached before and during the COVID-19 Pandemic.

3 Methodology

3.1 Dataset

The dataset used for this research are for the selected stock market in United States (NASDAQ and NYSE) and a European Stock market (EURONEXT 100) which were pulled from yahoo finance [2] pulled with yfinance[3] library in python[4] and we will be conducting an extensive analysis to understand the state of the market six months before COVID-19 (June 2019 - January 2020) and compare that to the effect of COVID-19 on the selected stock markets during the lockdown period (February 2020 - July 2020) and after post lockdown period (August 2020 till December 2020). These datasets were used for the GARCH volatility modelling. Also, we combined the dataset for the selected stock data before COVID-19 and during COVID-19 i.e (June 2019 – December 2020).

However, for each of the stock market we are considering, we define the value for the current price for the current day as P_t we also defined the stock value for the day before the current price is P_{t-1}. Therefore, we can define the daily

[2]Yahoo Finance: https://finance.yahoo.com/
[3]yFinance: https://pypi.org/project/yfinance/
[4]Pyrhon: https://www.python.org/

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returns as:

$$R_t = ln(P_t) - ln(P_t - 1) \tag{1}$$

3.2 Stationarity Test

A stationary time series data set is one whose attributes do not change over time. It is statistically defined as a series in which statistical properties such as autocorrelation, mean, and median remain constant over time. However, in most cases, time series are not stationary. As a result, it is critical to ensure that a time series is stationary prior to time series modeling. The Augmented Dicky Fuller (ADF) test will be used in this study to determine the level of stationarity in the time series. The ADF (Augmented Dicky Fuller) is defined as:

$$y_t = c + \beta t + \alpha y_{t-1} + \psi \Delta Y_{t-1} + et \tag{2}$$

Such that:

α is the coefficient of the first lag of Y.

$y_(t-1)$ is the first lag of the time series.

ΔY_{t-1} the first difference of the series at time $(t-1)$

3.3 Normality Test

A normality test is used to determine whether the data distribution resembles a normal distribution. It is simple to carry out a normal distribution around a normally distributed dataset. If a dataset is not normally distributed, a non-parametric statistic is used. When normalcy is not achieved, it is prudent to plot the data's histogram to determine whether or not the dataset contains outliers. In this study, we will use the Jacque-Bera (JB) test statistic to test the normality of the series we will be using for this research, which is defined as follows:

$$Jacque\ Bera = \frac{N}{6}\left(\text{Skewness}^2 + \frac{\text{Excess kurtosis}^2}{4}\right) \tag{3}$$

Skewness measures the level of distortion of a distribution while kurtosis describe how heavily tailed the considered distribution is compared to that of a normal distribution which can also be called the degree of peakedness.

3.4 Auto Regressive Conditional Heteroscedasticity (ARCH) Effects Test

To build a GARCH model with the series, it is prudent to consider the serial correlation within the heteroskedasticity. This means that we are trying to measure the correlation between the volatility of the series as it is measured by conditional variance in past innovations. As a result, the Lagrange multiplier (LM) test will be employed to measure the ARCH effect with a null hypothesis of "There is no ARCH effect in the series".

$$f(x, \lambda) = f(x) = \lambda g(x) \tag{4}$$

where:

$\lambda-$ Lagrange multiplier

$g(x)-$ equality constraint

$f(x)-$ function

$x-$ integer

Let ε_t denotes a time series' error term $\{X_t\}$. If the typical size of ε_t is characterized by stochastic piece u_t and time-dependent standard deviation σ_t then

$$\varepsilon_t = u_t \sigma_t \tag{5}$$

Where u_t is a stochastic piece of strong white noise and the time-dependent variance can be expressed as:

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \cdot + \alpha_p \varepsilon_{t-p}^2, \quad \alpha_0 > 0 \tag{6}$$

$$\alpha_t^2 = \alpha_i + \sum_{i=1}^{p} \alpha_i \varepsilon_{i-1}^2, \quad \alpha_i > 0, i > 0 \tag{7}$$

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where p is the length of ARCH lags. Considering the ARMA(pq) given as:

$$X_t - \alpha_1 X_{t-1} - \cdot - \alpha_p X_{t-p} = \epsilon_t - \beta_1 \epsilon_{t-1} - \cdot - \beta_p \epsilon_{t-p} \tag{8}$$

If we assume equation (8) for the error variance, we get

$$X_t = X'_{t-p} b + \epsilon_t \tag{9}$$

$$\alpha_t^2 = \omega + \alpha_1 \epsilon_{t-1}^2 + \cdot + \alpha_p \epsilon_{t-p}^2 + \beta_1 \sigma_{t-1} + \cdot + \beta_p \sigma_{t-q} \tag{10}$$

Thus, equation (5) can be written for $ARMA_{(pq)}$ as

$$\alpha_t^2 = \omega + \sum_{i=1}^{p} \alpha_i \epsilon_{t-1}^2 + \sum_{j=1}^{q} \sigma_{t-j}^2 \tag{11}$$

Equation (11) is the $GARCH_{(pq)}$ model.

3.5 Markov-Switching Dynamic Regression Model

Majorly in econometrics, in other to capture the regime shifts and its behavior, Markov-Switching autoregressive models (MSDR) model are always adopted. The MSDR model is an autoregressive time series models, which date back to [10] and [11] work, which characterize certain elements of the economic cycle. This econometric approach was also utilized by other academic researchers such as [12], [13], and [14] to simulate various economic variables such as exchange rates, interest rates, and stock returns.

The MSDR model as defined by [10] can be defined as the following:

Regime 0: $y_t = \mu_1 + \rho y_{t-1} + \varepsilon_t$

Regime 1 : $y_t = \mu_2 + \rho y_{t-2} + \varepsilon_t$

where y_t is the target variable,
μ_1 and μ_2 are known as the intercepts,
ρ indicates the autoregressive coefficient,
ε_t indicates the error term.

To calculate the transition matrix, the probability of moving from a stage to the other i.e (Stage i – Stage j) has to be known.

Therefore, the transition matrix is given below:

$$\begin{bmatrix} t_{11} & t_{12} \\ t_{21} & t_{22} \end{bmatrix} \tag{12}$$

where $T = \sum_{i=1}^{N-1} t_{t_i/j}$

4 Results

4.1 Volatility Modelling

According to the descriptive statistics in Table 1, there is a wide range between the minimum and maximum values of the daily returns of the closing prices of the NASDAQ, NYSE, and EURONEXT over the time period considered, i.e. before and during COVID-19. It was observed that the distribution of NASDAQ before COVID-19 and NYSE during COVID-19 are positive and moderately skewed, EURONEXT (before and during COVID-19) are positive and highly skewed while NASDAQ during COVID-19 and NYSE before COVID -19 are negatively skewed.
On the other hand, NASDAQ before and during COVID-19, and NYSE are found to be platykurtic while NYSE during COVID-19 and EURONEXT before and during COVID-19 are leptokurtic.

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Table 1: Descriptive Statistics of the Stock Returns

Index	Mean	Median	Min	Max	Standard Deviation	Skewness	Kurtosis
NASDAQ Before COVID-19	8322	8180	7333	9402	464	0.74	-0.32
NASDAQ During COVID-19	10266	10497	6860	12899	1492	-0.32	-0.76
NYSE Before COVID-19	12485	12651	8777	14516	1239	-0.47	-0.2
NYSE During COVID-19	3507265357	3459770000	1296540000	6454270000	618465246	0.9	5.12
EURONEXT Before COVID-19	182082767	176954500	31050800	405613400	48066284	1.12	4.76
EURONEXT During COVID-19	285906623	243144800	2933232	940519200	133727583	1.9	4.84

Figure 1 shows the time plots of NASDAQ, NYSE and EURONEXT which was considered during this research work. It was observed that there exists a very high volatility effect around February and June 2020 which is sometimes around the beginning of COVID-19 and the high rate of volatility might have been caused by the unexpected shock in the market due to COVID-19.

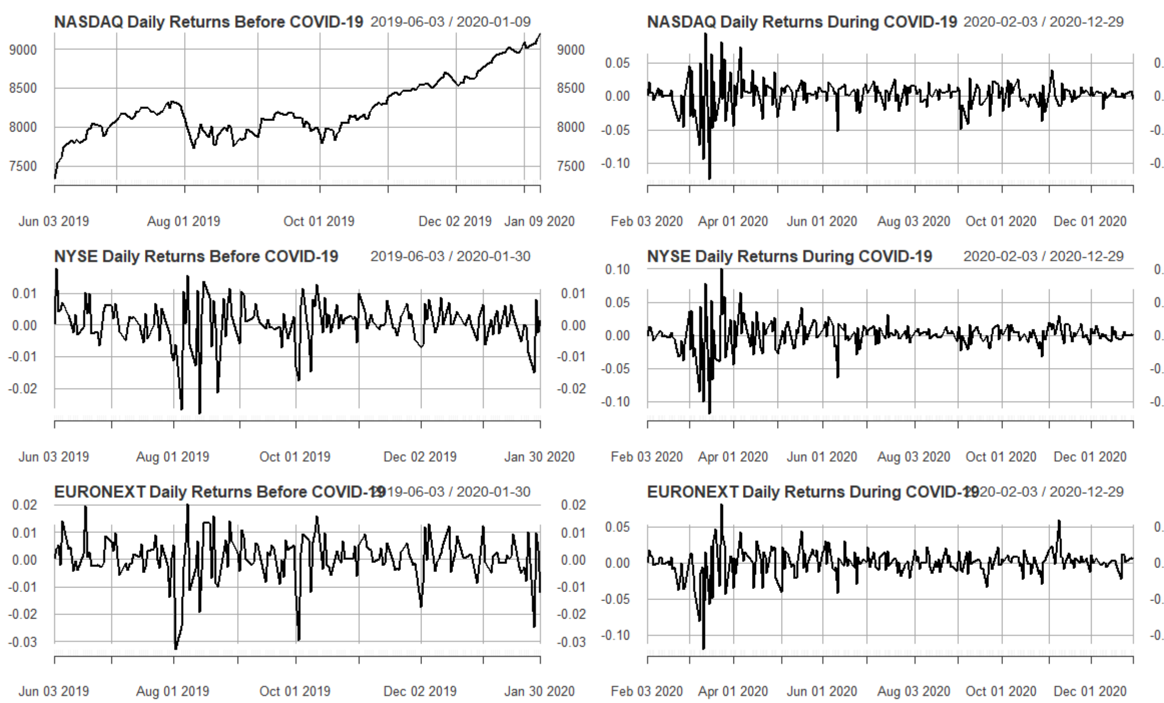

Figure 1: Time Plots of Daily Stock Returns (Before and After COVID-19)

Additionally, it is always helpful in time series/econometric modelling to confirm the stationarity and normality state of the indexes or data that is been considered. For this research work, we conducted an ADF and Jarque Bera Normality test in each of the indexes that was considered in this research. **??** below shows the estimate and the significance level of the test statistics.

Table 2: Stationarity and Normality Test

Index	Dickey-Fuller Statistics	P-Value & Jarque Bera	Statistics & P-Value	
NASDAQ Before COVID-19	-6.4934	0.01*	42.932	0.00**
NASDAQ During COVID-19	1-5.3573	0.01*	358.71	0.00**
NYSE Before COVID-19	-5.0553	0.01*	483.99	0.00*
NYSE During COVID-19	-5.7976	0.01*	111.23	0.00**
EURONEXT Before COVID-19	-5.4906	0.01*	99.939	0.00**
EURONEXT During COVID-19	-4.9174	0.01*	596.98	0.00**

Note: P-Values are in parenthesis and *, ** Statistically significant at the 5% and 1% significant level

Table 2 below shows the estimate and the significance level of the test statistics. The result of the Stationarity test shows that the p-value of the daily returns of all the stock returns are less than 0.05 which is statistically significant. We could therefore fail to accept the null hypothesis for the dickey fuller that states that the distribution of the returns are not stationary. This shows that we have clear evidence to conclude that the series are stationary. Also, the result of the Jarque Bera normality test shows that the p-value of all the stock index used are statistically significant at both 5% and 1% level of significance. This means that we fail to accept the null hypothesis and conclude that the distribution of the returns is normally distributed.

The autocorrelation plot of a series is also very important to check when it comes to financial econometrics modelling [15]. It helps to show how the observations of time t correlate with that of time t+k. The autocorrelation plot in Figure 2 show the correlation between the returns and log of returns of NASDAQ, NYSE and EURONEXT (For before and after COVID-19).

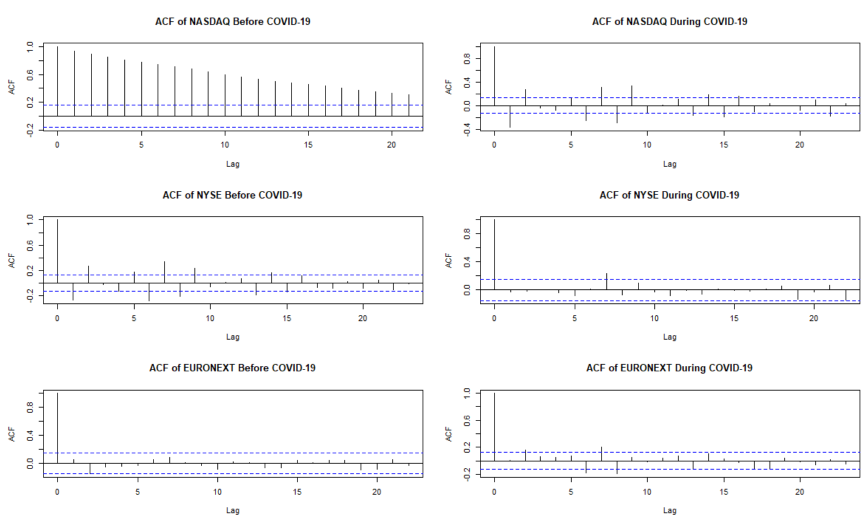

Figure 2: Autocorrelation Plots

This study employs a model order of p = 1 and q = 1 because it has been shown to be the best order for accurately fitting financial time series [1]. As shown in Table 3, the GARCH (1,1), examines previous volatility and current volatility

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before and after COVID-19. By considering the model output in Table 3 below, it was observed that all the estimate of NASDAQ, NYSE and EURONEXT before COVID-19 are all positive however, not all are statistically significant. The ARCH effect α in the table below shows how volatility responds to new information before COVID-19. It was observed that there is a low level of volatility effect during that period.We can also observe that the p-value of the estimate are statistically significant except that of EURONEXT. The results for β measures the persistent volatility of

Table 3: GARCH(1,1) Modelling Before COVID-19

	NASDAQ Before COVID-19	NYSE Before COVID-19	EURONEXT Before COVID-19
Intercept ω	0.0001 (0.307)	0.00004 (0.099)**	0.00001 (0.979)
ARCH α	0.186403 (0.00)**	0.2809 (0.0004)**	0.00002 (0.9002)
GARCH β	0.7563 (0.000)**	0.6476 (0.00)**	0.9990 (0.000)**
$\alpha + \beta$	0.9427	0.9285	0.99902

Note: P-Values are in parenthesis and *, ** Statistically significant at the 5% and 1% significant level

the indexes. As observed on the table above, it was shown that the coefficient of NASDAQ, NYSE and EURONEXT before COVID-19 are highly significant. Additionally, to this the coefficient of the volatility for NASDAQ and NYSE are 0.7563 and 0.6476 respectively which shows an indication of persistent volatility however there exist a very high persistent volatility for EURONEXT before COVID-19.
The addition of ARCH and GARCH effect measures the overall persistent volatility. As observed in the table above, EURONEXT has an extremely high persistent of the volatility before the beginning of COVID-19. This means that the return of the current day has a significant impact on the unconditional variance of many future periods. Equation 12 – 14 shows the model specification of the conditional volatility of GARCH (1,1) modelling for NASDAQ, NYSE and EURONEXT respectively before COVID-19.

$$\sigma_t^2 = 0.0001 + 0.1864\varepsilon_{t-i}^2 + 0.7563\sigma_{t-j}^2 \tag{13}$$

$$\sigma_t^2 = 0.00004 + \sum_{i=1}^{p} 0.2809\varepsilon_{t-i}^2 + \sum_{j=1}^{q} 0.6476\sigma_{t-j}^2 \tag{14}$$

$$\sigma_t^2 = 0.00001 + \sum_{i=1}^{p} 0.00002\varepsilon_{t-i}^2 + \sum_{j=1}^{q} 0.9990\sigma_{t-j}^2 \tag{15}$$

Table 4: GARCH(1,1) Modelling During COVID-19

	NASDAQ During COVID-19	NYSE During COVID-19	EURONEXT During COVID-19
Intercept ω	0.000032 (0.006)**	0.00001 (0.400)	0.00001 (0.0036)**
ARCH α	0.2666 (0.001)**	0.2694 (0.0035)**	0.2078 (0.0025)**
GARCH β	0.6977 (0.000)**	0.7206 (0.000)**	0.7556 (0.000)**
$\alpha + \beta$	0.9643	0.99	0.9634

Note: P-Values are in parenthesis and *, ** Statistically significant at the 5% and 1% significant level

For the volatility measurement during COVID-19, the ARCH effect in Table 4 shows how volatility responds to new information during COVID-19. By comparing the output of the ARCH effect during COVID-19 with the one before COVID-19, we will observe that there exist of higher volatility responds for NASDAQ, NYSE and EURONEXT. The cause of the response might be as a result of the information of COVID-19 that started in the early months of 2020. In addition to this, it was also observed that all the coefficients are statistically significant for NASDAQ, NYSE and EURONEXT before COVID-19.

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The output of the GARCH effect shows the measurement of the persistence of the volatility. Based on comparison, only NYSE has a higher persistence of volatility while NASDAQ and EURONEXT GARCH coefficient has dropped.
The overall level of persistence which is measures by the addition of ARCH and GARCH effect for NASDAQ and NYSE increased which might be due to the cause of COVID-19 while the reason of the drop in the GARCH effect for EURONEXT might be due to other factors.
Equation 15 – 17 shows the model specification of the conditional volatility of GARCH (1,1) modelling for NASDAQ, NYSE and EURONEXT respectively during COVID-19.

$$\sigma_t^2 = 0.000032 + 0.2666\varepsilon_{t-i}^2 + 0.6977\sigma_{t-j}^2 \tag{16}$$

$$\sigma_t^2 = 0.00001 + \sum_{i=1}^{p} 0.2694\varepsilon_{t-i}^2 + \sum_{j=1}^{q} 0.7206\sigma_{t-j}^2 \tag{17}$$

$$\sigma_t^2 = 0.00001 + \sum_{i=1}^{p} 0.2078\varepsilon_{t-i}^2 + \sum_{j=1}^{q} 0.7556\sigma_{t-j}^2 \tag{18}$$

4.2 Model Diagnostics

The result from Figure 3 shows that the fitted residuals for NASDQ before and during COVID-19 are not normally distributed. The fitted density of NASDQ before COVID-19 deviate a bit from a normal distribution while that of NASDQ during COVID-19 is rightly skewed and too peaked in the middle.

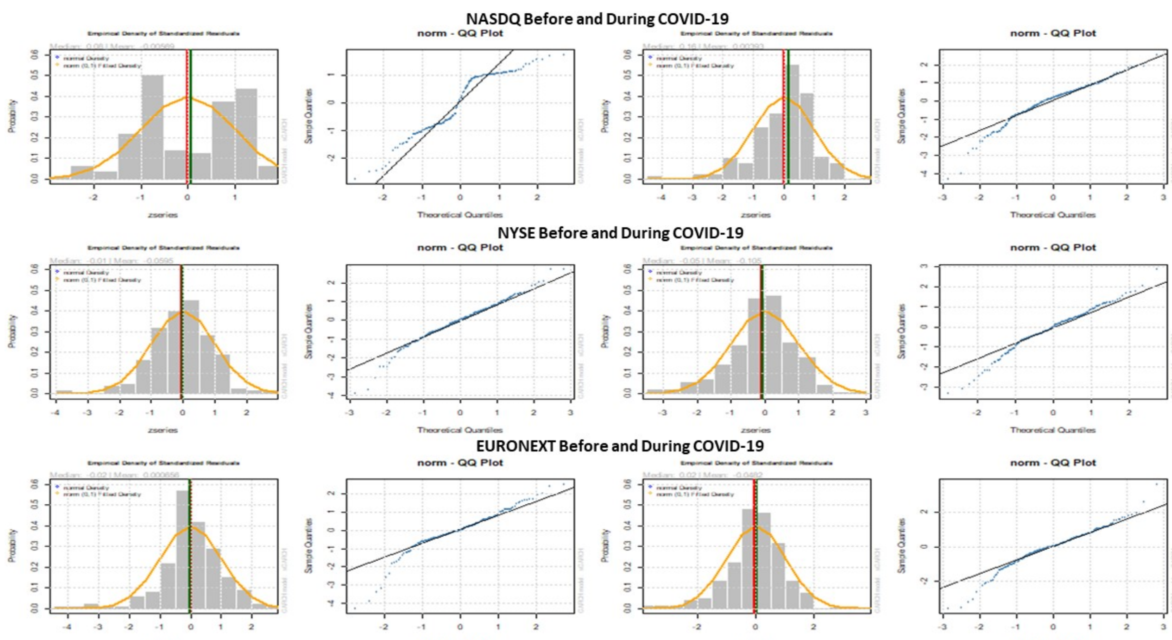

Figure 3: Model Diagnosis of GARCH (1,1) for NASDQ, NYSE and EURONEXT, Before and During COVID-19

The diagnostic result of NYSE of shows that the density of the standardized residual is close to normally distributed but too peaked in the middle. Also, the QQ-plots shows a thin tail both for before and during COVID-19.
The diagnostic result of the shows that the distribution for the standardized residual for EURONEXT before COVID-19 is right skewed while the QQ-plot has a thin tail. And on the other side, standardized residual for EURONEXT during COVID-19 it was observed that the distribution follows a normal distribution even though it was too peaked in the middle while the QQ-plot also shows a thin tail.

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4.3 Markov-Switching Dynamic Regression

In this section of the research employ the Markov-Switching Dynamic Regression (MSDR) with a two-state regime to determine the regime states for the NASDQ, NYSE, and EURONEXT from June 2019 to December 2020. Table 5 shows the calculated parameters for the two states of regimes.

The computed coefficients of the regime switching models are shown in Table 5 below. It was discovered that μ_1 and μ_2 are estimated coefficients with constant probability, where regime 0 and regime 1 represent (calm/low and risky/high) regimes. According to these findings, the predicted coefficients of the regime switching models are larger in Regime 0 than in Regime 1. This means that the probability to stay in regime 0 is higher than the probability of staying in regime 1, suggesting that regime 0 is more persistent than regime 1. In other words, regime 0 which is low/calm is more stable and markets spend more time in this regime than in regime 1 which is high/risky for NASDQ, NYSE and EURONEXT indexes.

Table 5: MSDR Model Summary

Index	NASDAQ	NYS	EURONEXT
μ_1	0.0026	0.0014	0.0010
	(0.00)**	(0.002)	(0.051)
μ_2	-0.0025	-0.0012	-0.0016
	(0.525)	(0.660)	(0.569)
σ_1	0.0013	0.0009	0.0008
	(0.00)**	(0.000)	(0.00)
σ_2	0.0619	0.029	0.044
	(0.00)**	(0.000)**	(0.00)**
t_{11}	0.9777	0.9735	0.9824
t_{22}	0.0840	0.0650	0.0538

Note: P-Values are in parenthesis and *, ** Statistically significant at the 5% and 1% significant level

Furthermore, we define the mechanism that explains how to transition from regime 0 to regime 1. This is possible because to the Markov transition matrix, which holds the odds of switching from one regime to another[16].

Table 6: Transition probabilities of switching between Low and High Regimes

	NASDAQ		NYSE		EURONEXT	
	Reg. 0,t	Reg. 1,t	Reg. 0,t	Reg. 1,t	Reg. 0,t	Reg. 1,t
Reg. 0	0.9777	0.0840	0.9735	0.0650	0.9824	0.0538
Reg. 1	0.0223	0.916	0.0265	0.935	0.0176	0.9462

Note that $\sum_{i=1}^{N-1} \frac{t_i}{j} = 1$

The result in Table 6 shows that for NASDQ the probability to move from regime 1 to regime 0 is 8.4% however there is a low probability of migrating 2.22%. For NYSE the probability of migrating from regime 1 to regime 0 is 6.5% which is higher than the probability of moving. Also, for EURONEXT the probability to move from regime 1 to regime 0 is 5.4% however there is a low probability of migrating 1.7%.
In addition, to aid decision making of the various regimes, the Smoothed Regime Probabilities are presented in Figure 4 below for NASDQ, NYSE and EURONEXT.

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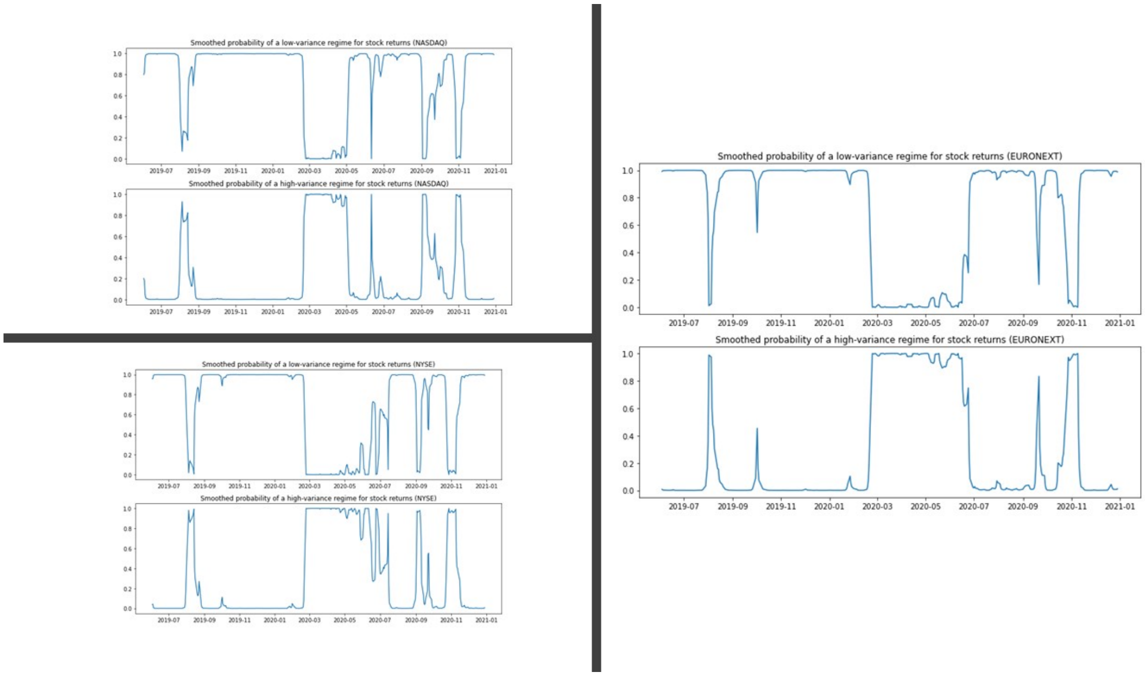

Figure 4: Smoothed Regime Probabilities

Furthermore Figure 5 shows the chart that separate high volume and low volume market regimes for NASDQ, NYSE and EURONEXT.

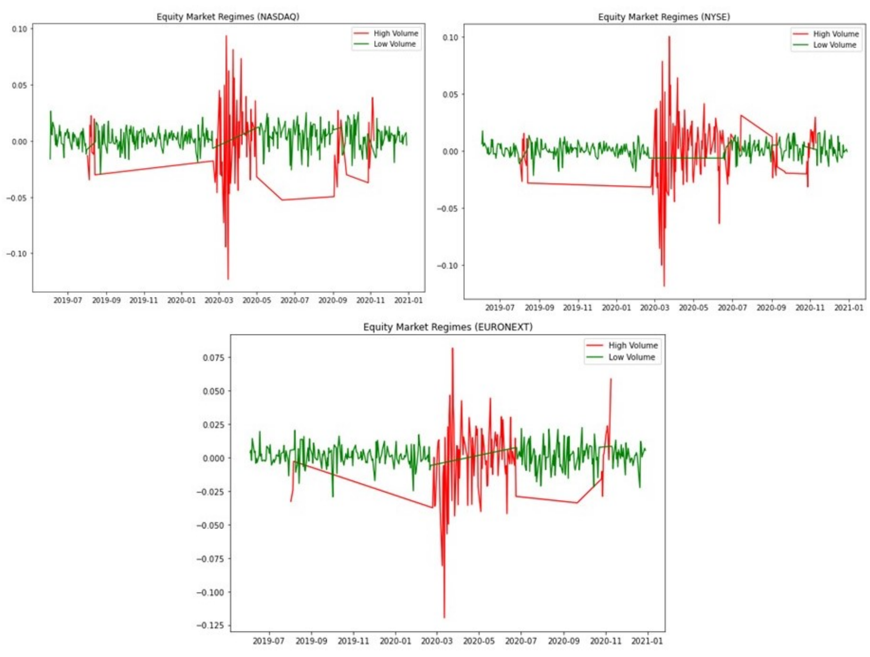

Figure 5: Classification of Low and High Market Regimes

Finally, it was observed based on the output of Figure 5t that the most critical stage of volatility for NASDQ, NYSE and EURONEXT were around March 2020, which was around the same time Europe and the United States imposed COVID-19 lockdown.

5 Conclusion

This project work focuses empirical analysis, of measuring the extent of volatility of the United States (NASDAQ and NYSE) and European stock market (EURONEXT). These datasets were collected for the period before COVOD-19 (2019-06-01 to 2020-01-31) and during COVID-19(2020-02-01 to 2020-12-30).
A preliminary analysis was carried out on the data in other to understand the nature of the data used. The dataset was tested for normality and stationarity and all assumptions were met before modelling. The result of the GARCH (1,1) model of NASDAQ and NYSE before COVID-19 shows that there exists a low volatility effect however EUONEXT was shown to have a very high persistent volatility before COVID-19. By comparing the result of NASDAQ and NYSE before COVID-19 with that of GARCH(1,1) after COVID-19, it was observed that the overall persistent volatility is very high which might be due to the cause of COVID-19 while the reason of the drop in the GARCH effect for EURONEXT might be due to other factors. The results for GARCH (1,1) (both before and after COVID) implied that volatility shocks had a high persistence for NASDAQ, NYSE, and EUONEXT returns, and that the magnitude of volatility spillover is positively related and highly significant. This implies that volatility existed prior to COVID-19, but the rate of volatility increased after COVID-19, possibly as a result of the COVID-19 shock. The result of MSDR shows that the probability to stay in regime 0 (calm/low) is higher than the probability of staying in regime 1 (risky/high) for NASDAQ, NYSE and EURONEXT. However, in other to create more evidence around the high persistent volatility during COVID-19, MSDR model was able to confirm in figure 4.5 that there exist an higher volatility which is due to unexpected shock of COVID-19. Finally with the use of the transition probabilities understand the possibilities of moving from regime 0 (calm/low) to regime 1(risky/high) and vice versa.

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