Investigating Market Risk and Spillover Effects of Caribbean and Cryptocurrency Markets During the Pandemic

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Abstract

Over the last two years, financial markets experienced periods of adverse instability due to the ramifications of the COVID-19 pandemic. Global economic growth rates fell tremendously low. Investors were required to seek alternative avenues to mitigate potential losses. Although the cryptocurrency market experiences high volatility; investors have been attracted to it. This study aims to evaluate the market risk of the selected Caribbean markets and cryptocurrencies prior to and during the pandemic by utilizing the Value at Risk (VaR) methodology. The results concur with the literature as the confidence interval decreases the expected loss increases. Additionally, the study examines the spillover effect of cryptocurrencies on Caribbean equity markets through the Vector Autoregressive Model (VAR). The results indicate that there is no substantial spillover effect present between equity and cryptocurrency markets.

Introduction

The novel coronavirus (2019-nCOV) or COVID-19 was first detected in Wuhan City, Hubei Province of China in December 2019 (WHO, 2020). The rapid spread of COVID-19 escalated to the state of a world pandemic. As of April 2022, there has been approximately 511 million persons infected with COVID-19 and roughly 6.2 million lives have been lost. Based on the data reported via Reuters, Latin America and the Caribbean has experienced at minimum 68.194 million reported infections and 1.681 million reported deaths. Most of the Caribbean islands reported their first COVID-19 cases within the month of March 2020. As the countries experienced increasing daily infections as well as deaths, the relevant authorities were forced to implement restrictions and lockdown measures ranging from no movement days, essential services only and shutting down of various sectors of the economy to curb the rate of infection and death toll. The enforcement of these restrictive measures led to halting of various economic activities thus inevitably affecting individuals, businesses, and governments. The financial markets were not left untouched as the pandemic intensified thus increasing the level of uncertainty especially within the stock markets.

As an investor, the level of uncertainty also known as the risk involved influences how trading is conducted presently and in the future. The stock market crash of 2020 triggered by the rampant economic consequences of the COVID-19 restrictions led to significant shocks to the well-known Dow Jones Industrial Average which plummeted nearly 3,000 points representing a loss of 12.9% on March 16th, 2020. The drop in stock prices was considerably immense causing the New York Stock Exchange (NYSE) to halt trading several times. The Caribbean stock exchanges such as the Barbados Stock Exchange (BSE), Eastern Caribbean Stock Exchange (ECSE), Jamaica Stock Exchange (JSE) and Trinidad and Tobago Stock Exchange (TTSE) cannot be compared to that of international stock exchanges such as the New York Stock Exchange (NYSE), Toronto Stock Exchange (TSX) or London Stock Exchange (LSE).

There has been increasing interest among academics, investors, speculators, and portfolio managers toward the recent digital asset class known as cryptocurrencies. However, literature directly related to the Caribbean has been limited. As an investor, understanding how the COVID-19 pandemic has affected the market risk of the Caribbean based stock markets in comparison to cryptocurrency markets is critical in making future informed investments. The spillover effects in both markets are considered equally important as well. In both cases, it is beneficial to assess the impact not only at the beginning of the pandemic but also in prior periods and to compare the nature of this impact.

Market risk refers to the risk of gain or loss occurring from unanticipated changes in market prices or market rates (Dowd, 2003). Over the years, the VaR methodology has been a popular method of quantifying market risk associated with cryptocurrencies and equity markets. The market crash induced by the COVID-19 pandemic induced a stir within the markets and resulted in investors becoming speculative of their investment options (Giglio et al, 2021). Market risk affects the performance of the entire market and cannot be differentiated through diversification. Although, portfolio diversification cannot eradicate systematic risks such as market risk; investors are urged to diversify their portfolios to control the degree of losses experienced. In times of impulse events, investors holding diversified portfolios can still manage to maximize their returns. The popular proverb states "Do not put all of your eggs into one basket". The literature suggests that assets become more correlated during economic downturns (Goodell et al, 2020).

This study contributes to the literature by evaluating the impact of COVID-19 on the market risk of selected Caribbean markets through the application of VaR models. Additionally, this study examines the spillover effect of cryptocurrencies on Caribbean equity markets through the application of a vector autoregressive model (VAR). The remainder of the paper is structured as follows: Section 2 will examine some of the past literature surrounding this study. Section 3 will provide an outline of the methodological framework used in this study. Section 4 will report the results and discuss the findings of the study. Section 5 will provide the conclusion of this study.

Literature Review

History of Money Development

The inception of the money evolution began with barter known as the exchange of goods and services for other goods and services (Shah, 2020). The first record of bartering can be traced back to Egypt. However, in the barter economy, the issue of double coincidence of wants surfaced (Starr, 1972). Although, barter was inconvenient, it embodied a significant step forward from a state of self-sufficiency in which every man had to be a jack of all trades and master of none (Samuelson, 1973). Subsequently, there was commodity money, metallic money, paper money, plastic money, and electronic money. Commodity money describes money whose value comes from the commodity of which it is made such as shells, gold, silver, grains, salt, copper, alcohol, and cocoa. Around 1100BC, the use of small replicas of goods from bronze emerged in China. The first official currency was minted in Lydia which is now known as Turkey (Velde, 1998). Later, there was the movement from coinage to paper money; presently called fiat currency. This was followed by the introduction of the plastic money in the form of debit and credit cards which then led to the present era of electronic money such as digital currencies and cryptocurrencies (Fork, 2017). Many governments are working in collaboration with their banks to create an appropriate Central Bank Digital Currency (CBDC).

Firstly, cryptocurrencies are a subset of digital currencies. Digital currency is any currency that is exclusively available in electronic or digital form. It is important to note that the terminology digital currencies and cryptocurrencies is sometimes used interchangeably. However, cryptocurrencies are only a subset of digital currencies whereas digital currencies can also refer to electronic money and virtual currencies. Unlike traditional forms of money, cryptocurrencies do not satisfy the fundamental functions of money, that is, unit of account, store of value, medium of exchange and standard of deferred payment. Electronic currencies are operational from any device connected to the internet; cryptocurrencies can easily fulfil the monetary role of medium of exchange. However, it is one thing to technically fulfil that role, but finding demand for being used as a medium of exchange is a different question, enhanced by obtaining demand as a store of value or unit of account. Cryptocurrencies are currently wholly inadequate as a unit of account due to fluctuating demand and inflexible supply, and the absence of an authority that can manage the supply to maintain a constant value.

Market Risk and Value at Risk (VaR)

Managing risk is relevant to all investors and companies. Market risk is something all investments are exposed to when one or more market variables such as interest rate, equity price, commodity prices or exchange rates change significantly (Haughey and Bychuk, 2011). Hence, managing risks is a relevant area of study. Market risk can also be defined as the risk or loss (or gain) arising from unexpected changes in the market prices or rates (Dowd, 2003). There are different types of market which also encompasses changes or movements in interest rates, exchange rates and commodity prices. Most commonly, market risk is measured by employing the Value at Risk model. This was known as RiskMetrics which was developed by JP Morgan. The RiskMetrics system originated due to the demand for a one-page report also called the "4:15 report" indicative of the risk and potential losses over the following 24 hours across the bank's entire trading portfolio. In order to satisfy this demand, a system was developed to obtain a single measure that aggregated the measured risks across different trading positions and institutions. The single measure was called the Value at Risk (VaR) and was developed by JP Morgain in 1996.

Value at Risk commonly abbreviated as VaR became the popular financial metric that is used to estimate the maximum risk of an investment over a specified period. VaR is easy to understand, applicable to all asset types and is universally accepted as a measurement of risk when trading and advising on assets. According to Jorion (2001), "VaR measure is defined as the worst expected loss over a given horizon under normal market conditions at a given level of confidence. For instance, a bank might say that the daily VaR of its trading portfolio is $1 million at the 99 percent confidence level. In other words, under normal market conditions, only one percent of the time, the daily loss will exceed $1 million."

There are three main categories of VaR models: non-parametric (historical simulation), parametric (variance-covariance approach), and semi-parametric (Filter Historical Simulation, Extreme Value Theorem (EVT), CAViaR (Conditional Autoregressive VaR), Monte Carlo Simulation). The historical simulation which is categorized as a non-parametric approach is the simplest to implement since there are minimal assumptions made concerning the error distribution. It has been criticized since it only allows the estimation of VaR at discrete confidence intervals and does not properly demonstrate major events. The parametric and semi-parametric approaches have proposed improved method which are Risk Metrics and the Filtered Historical Simulation respectively. Risk Metrics is applicable when a normal distribution or student t-distribution is assumed. Meanwhile, the Filter Historical Simulation is like the non-parametric Historical Simulation in ease of implementation but additionally volatility is taken into consideration. The literature suggests that Filtered Historical Simulation is usually superior (Marimoutou et al, 2009; Zikovic and Aktan, 2009; Giamouridis and Ntoula, 2009; Angelidis et al, 2007; Bao et al, 2006; Kuester et al, 2006).

The parametric approach also benefits from easy implementation and can be estimated using different distributions such as the normal distribution, t-Student distribution, skewed t-Student distribution, mixed normal distribution, and high-order moment time-varying distribution. Sener et al (2012) and Alonso and Aeros (2006) deemed that the parametric approach utilizing the normal distribution was the best method to estimate VaR. Whilst Abad and Benito (2013) indicated that the t-Student distribution was the best. Moreover, Sener et al (2012), Polanski and Stoja (2010) achieved the best VaR when applying the high-order moment time-varying distribution. With respect to the semi-parametric approach, numerous studies have ruled the EVT as the best to properly measure risk (Ergun and Jun, 2010 and Raei et al, 2010)

Value at Risk models have been utilized in assessing the market risk of many developed stock exchanges (Chen, 2013; Bali & Cakici, 2004 and Shaik & Padmakumari, 2022). However, its application to Caribbean markets has not been as prevalent. Rampersad & Watson (2009) evaluated the efficacy and applicability of VaR models in the emerging equity markets of the Caribbean (BSE, ECSE, JSE and TTSE). It was concluded that the parametric VaR was the most effective in all markets. Many research papers that employed the VaR of cryptocurrencies focused on Bitcoin such as Kwon (2021) and Conlon et al (2020).

Some researchers have stated that VaR is not a coherent market measure (Artzner et al, 1999) because it does not satisfy the subadditivity condition and may dissuade diversification. Therefore, one the methods utilized to examine the accuracy and appropriateness of VaR models is back testing. Zhang & Nadarajah (2017) provided a wide-ranging review of back testing methods which began with the simplest back testing method. Other less statistically intense methods that can be applied include the calculation and interpretation of Mean Squared Error (MSE), Mean Absolute Deviation or Error (MAD or MAE) and Mean Absolute Percent Error (MAPE). The Conditional VaR (CVaR) also known as the Expected Shortfall (ES) is considered a coherent measure of risk with the exception being non-continuous distributions.

Spillover Effects of Cryptocurrency on Equity Markets

In the field of economics, the analysis of the spillover effect is quite popular. The spillover effect describes how unrelated events happening in another country impact the economy of another country such as natural disasters, pandemics, and political crises (Sweta, 2022). The literature has indicated that there has been an understatement of stock market volatility between different stock markets. The vector autoregressive model (VAR) is commonly applied to properly assess spillover effects through a combination of either impulse response and variance decomposition or both. Many studies have examined the spillover effects of cryptocurrencies (most popularly Bitcoin) on developed equity markets (Trabelsi, 2018 and Cao & Xie, 2022)

The GARCH family of econometrics is another very popular method in the examination of spillover effects especially regarding financial markets and assets. Firstly, the GARCH-BEKK is commonly used for examining the spillover effect between stock markets (Liu, 2016; Dehbashi et al, 2022; Mishra et al, 2022), cryptocurrencies and (Rastogi and Kanoujiya, 2022). Another popular variation is the Coupla-DCC-GARCH model used for cryptocurrencies (Chen and Chang, 2022). Generally, the studies using VAR and GARCH models conclude that cryptocurrency markets particularly Bitcoin has statistically significant spillover effects to equity markets. Most of the published focused on developed equity markets.

Methodology

The methodology is subdivided into two parts:

(i) The examination of market risk through the VaR framework

(ii) The investigation of spillover effect and volatility using VAR and GARCH models respectively

Value at Risk (VaR)

The VaR approach was employed to examine the risk experienced by each stock exchange index. In particular, the historical, parametric, and modified approaches were utilized. For each of the three approaches, the VaR and Conditional VaR (CVaR) also known as the Expected Shortfall (ES) were calculated at the 1%, 5% and 10% level of significance for each sub-period.

The most common and simplest method of VaR estimation is the historical method. The historical method is a non-parametric method and therefore, the distribution does not have to conform to specific properties. The index returns are ranked in ascending order. The VaR is calculated based on the selected confidence interval. The CVaR or ES is the average of the returns that exceed the VaR.

The parametric approach assumes that the returns are normally distributed, that is, has a mean of zero and standard deviation of 1, N (0,1). This follows a Gaussian distribution. The VaR is calculated using the following:

$$VaR_\alpha = -(\mu + z_\alpha \sigma) \quad (1)$$

where $z_\alpha = N^{-1}(\alpha)$, μ represents the mean return, σ represents the standard deviation, α is the confidence interval and $N^{-1}(.)$ is the inverse cumulative normal distribution.

The CVaR or ES is calculated using the following:

$$CVaR_\alpha = -(\mu + Z_\alpha \sigma) \quad (2)$$

where $Z_\alpha = \frac{1}{\alpha} \times \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}z_\alpha^2}$, μ represents the mean return, σ represents the standard deviation, α is the confidence interval and Z is the percentile point of the standard normal distribution.

The modified approach incorporates the skewness and kurtosis of the returns using the Cornish-Fisher Expansion (CFVaR). The VaR is calculated using the following:

$$MVaR_\alpha = -(\mu + w_\alpha \sigma) \quad (3)$$

where $w_\alpha = z_\alpha + (z_\alpha^2 - 1)\frac{S}{6} + z_\alpha (z_\alpha^2 - 3)\frac{K}{24} - z_\alpha (2z_\alpha^2 - 5)\frac{S^2}{36}$, S represents the skewness and K represents the excess kurtosis.

The CVaR or ES is calculated using the following:

$$MCVaR_\alpha = -(\mu + W_\alpha \sigma) \quad (4)$$

where $W_\alpha = \frac{1}{\alpha} \times \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}z_\alpha^2} \left[1 + z_\alpha \left(\frac{S}{6}\right) + (1 - 2z_\alpha^2)\left(\frac{S^2}{36}\right) + (-1 + z_\alpha^2)\left(\frac{K}{24}\right)\right]$, S represents the skewness and K represents the excess kurtosis.

Vector Autoregressive Model (VAR)

The general form of a VAR is shown below:

$$V_t = \sum_{i=1}^{m} A_i V_{t-i} + \epsilon_t \tag{5}$$

Where: V_t contains all the variables of the model and ϵ_t is a vector of the random errors.

The utilization of a VAR model in this application allows for the segmentation of the impact caused by shocks of each variable into the long-term and short-term. The VAR model allows for the analysis of shocks which are segmented into endogenous (idiosyncratic) shocks and exogenous shocks from a particular variable. The VAR comprises of two types of variables: exogenous and endogenous variables. In this paper, the exogenous variables are the selected cryptocurrencies: BTC, ETH, USDT, BNB, ADA along with the stock exchanges: BSE, JSE and TTSE whilst the endogenous variable is a constant. The constant is selected as the endogenous variable because it allows the examination of the impact on the dependent variable experienced by changes in the level of return within the equity and cryptocurrency markets. The VAR requires that its variables are stationary and can be utilized for forecasting.

Generalized Autoregressive Conditional Heteroskedasticity (GARCH)

To apply generalised autoregressive conditional heteroskedasticity (GARCH) modelling to a financial time series, there must be the presence of an autoregressive conditional heteroskedasticity (ARCH) effect (Ekong & Onye, 2017). This is determined by testing the significance of the coefficient. The heteroscedasticity ARCH LM test allows the testing of each stock to establish whether there is an ARCH effect present (Engle, 1982).

The hypotheses are as follows:

H_0: ARCH effect is not present ($\alpha_i = 0$)

H_1: ARCH effect is present ($\alpha \neq 0$)

Significance level: 5%

Decision Rule: If probability < 0.05, Then Reject H_0

No ARCH effect suggests that a GARCH model cannot be applied and would not sufficiently represent the time series data. This usually occurs when a stock or cryptocurrency exhibits low variability in prices and by extension returns. Furthermore, this suggests that the stock or cryptocurrency is not extremely responsive or sensitive to shocks or fluctuations in the market. Once an ARCH effect was present, the following three types of the GARCH models were applied to each stock: ARCH (1), GARCH (1,1) and TGARCH (1,1,1).

The GARCH (1,1) is the most used volatility model (Ekong & Onye, 2017). The GARCH (1,1) model is shown below:

$$\sigma_t^2 = \omega + \alpha x_{t-1}^2 + \beta \sigma_{t-1}^2 \tag{6}$$

where ω, α, β ≥ 0 and α + β < 1

In this model, alpha measures the extent to which volatility shocks today feeds through into next period's volatility. The value of beta is interpreted as an impact of the past value of volatility on today's volatility. To satisfy the condition of stationarity, the summation of alpha and beta should be less than one. The summation is occasionally referred to as the volatility persistence and measures the rate at which the effect dies out over time. Persistence of volatility occurs when the summation of alpha and beta equals to one, thus implying that the long run variance will tend towards infinity, suggesting that the shocks die out slowly (Bollerslev, 1986). This indicates that the process is not stationary in nature and should be possibly modelled using an integrated generalised autoregressive conditional heteroskedasticity (IGARCH) model. In this case, the unconditional variance becomes infinite. The value that is achieved when running the threshold generalised autoregressive conditional heteroskedasticity (TGARCH) model represents the fatness of the distribution tail and is documented as gamma.

According to Ahmed and Suliman (2011), a non-zero value of gamma indicates that the returns are asymmetric in nature. However, the standard symmetric GARCH model is achieved when gamma is equal to zero and a leverage effect exists when gamma is positive. The TGARCH (1,1) model is shown below:

$$\sigma_t^2 = \omega + \alpha x_{t-1}^2 + \delta D_t x_{t-1}^2 + \beta \sigma_{t-1}^2 \tag{7}$$

where $D_{t-1} = \begin{cases} 1, & x_{t-1} < 0 \\ 0, & x_{t-1} \geq 0 \end{cases}$

An analysis of the coefficients between the stock exchanges is performed. The stationarity of the GARCH and TGARCH models is also investigated to determine whether the models satisfy the stationary condition.

Data Analysis

Data

The objective of this study is to examine the return and volatility spillover effects between equity markets in the Caribbean namely Barbados, Jamaica and Trinidad and Tobago and cryptocurrency markets. Additionally, the empirical analysis aims to identify whether there was a difference in market interdependence prior to and during the COVID-19 pandemic. The dataset consists of daily market indices of the BSE, JSE, TTSE, Bitcoin (BTC), Ethereum (ETH), Tether (USDT), Binance Coin (BNB) and Cardano (ADA). The dataset spans 01 March 2018 – 28 February 2022. The dataset employed in this study only includes the days in which all markets were open for trading. Each market apart from the cryptocurrency market was closed on weekends and public holidays such as the National Heroes Day renowned on April 28th in Barbados, Labour Day celebrated on June 19th in Trinidad and Tobago and Independence Day recognized on August 6th in Jamaica. Consequently, the daily market indices may not match with each other. This approach was utilized by Hamao, Masulis and Ng (1990) and Liu (2016). Hamao, Masulis and Ng (1990) stated that once no trading exists in one market on a particular date in the model, then the data of that date should be excluded for the remainder of the markets whether there was trading or not.

Selection of the Sample Markets and Periods

The purpose of this study is to identify the volatility spillover between the top cryptocurrency markets and Caribbean equity markets. The major Caribbean stock exchanges (Barbados, Jamaica and Trinidad and Tobago) were preferred as a proxy for the Caribbean since these were the major equity markets in this region and the corresponding main index data were easily available. Based on the market capitalization, the top 5 cryptocurrencies were BTC, ETH, Tether, BNB, and ADA were chosen to represent the cryptocurrency market.

The three selected countries experienced their initial cases of COVID-19 within the month of March 2020. As restrictive measures were implemented and financial markets experienced instability, investors explored their options for various mechanisms to enhance their portfolio. All investors would benefit from understanding return and volatility spillover and the impact of COVID-19 on the intensity of the spillover effects. The sample period is separated into two sub-periods: pre-COVID (01 March 2018 – 28 February 2020) and during COVID (01 March 2020 – 28 February 2022).

Initially, the daily prices of the main stock indices were downloaded from the respective stock exchange website. The main application utilized in the manipulation and analysis of the stock indices were Microsoft Excel and EViews. A simple mathematical calculation was performed to compute the daily returns of each stock index using the formula: $R_t = ln\left(\frac{P_t}{P_{t-1}}\right)$ where R_t represents today's return, that is, the return at time t, P_t represents today's price, that is, the price at time t, P_{t-1} represents yesterday's price, that is, the price at time t-1. The logarithm of each variable is taken to ensure that the data is time consistent and less skewed.

Descriptive Statistics

Each variable is divided into the two subperiods mentioned above and the statistical properties are calculated. The statistical properties included: mean, variance, standard deviation, skewness, and kurtosis. Table 1 and Table 2 presents the descriptive statistics of the pre-COVID and during COVID periods in that order.

Prior to COVID, all selected stock exchanges and cryptocurrency markets experience positive average return which is like the experience in other markets except for BTC and ADA. This is expected since market volatility was stable before COVID. Based on the all the selected markets in this study, the BTC market suffered the highest average daily loss (-0.05%) whilst the BNB market observed the highest average daily return (0.12%). Amongst the Caribbean stock markets, JSE and BSE has the highest and lowest average return at 0.11% and 0.00% respectively. Among the cryptocurrency market, BTC had the smallest loss (-0.05%) and ADA had the largest loss (-0.39%). The largest and lowest gain was observed by BNB and USDT. BSE experienced the highest volatility at 1.01% among the stock markets. However, this incomparable to the lowest which is USDT (0.46%) and highest which is ADA (6.42%) observed by the cryptocurrency markets. Therefore, it can be stated that TTSE and USDT are the most stable stock and cryptocurrency markets respectively.

During the pandemic, TTSE was the only stock market of the three that maintained a positive average daily return (0.02%). JSE decreased from 0.11% to -0.04% and BSE from 0.00% to 0.07%. For the cryptocurrency markets, USDT remained unchanged. BTC (-0.05% to 0.34%), ETH (-0.29% to 0.54%) and ADA (-0.39% to 0.63) experienced positive average returns although the opposite for true prior the pandemic. BNB maintained positive returns and increased from 0.12% to 0.64% during the pandemic. In terms of stock market volatility, JSE and TTSE increased whilst BSE decreased. The volatility of all the cryptocurrency markets increased apart from USDT which remained unchanged.

Table 1. Descriptive Statistics (Pre-COVID)

Pre-COVID	BSE	JSE	TTSE	BTC	ETH	USDT	BNB	ADA
Mean	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Median	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Maximum	0.07	0.05	0.03	0.20	0.18	0.02	0.28	0.25
Minimum	-0.10	-0.03	-0.01	-0.16	-0.21	-0.02	-0.19	-0.19
Std. Dev.	0.01	0.01	0.00	0.04	0.06	0.00	0.06	0.06
Skewness	-1.78	0.56	2.18	0.01	-0.25	0.15	0.43	0.13
Kurtosis	41.03	6.67	22.87	5.82	4.57	5.95	5.54	4.16
Jarque-Bera	28454.47	287.59	8071.04	154.74	53.19	170.96	140.69	27.48
Probability	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Sum	0.01	0.51	0.13	-0.23	-1.35	0.00	0.58	-1.83
Sum Sq. Dev.	0.05	0.03	0.00	0.91	1.47	0.01	1.68	1.92
Observations	468	468	468	468	468	468	468	468

Table 2. Descriptive Statistics (During COVID)

COVID	BSE	JSE	TTSE	BTC	ETH	USDT	BNB	ADA
Mean	0.00	0.00	0.00	0.00	0.01	0.00	0.01	0.01
Median	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00
Maximum	0.06	0.05	0.03	0.24	0.49	0.05	0.53	0.60
Minimum	-0.06	-0.05	-0.02	-0.46	-0.55	-0.05	-0.54	-0.50
Std. Dev.	0.01	0.01	0.00	0.05	0.07	0.00	0.08	0.08
Skewness	-3.49	-0.46	0.41	-1.40	-0.54	0.45	-0.03	0.63
Kurtosis	84.73	10.28	8.84	18.88	17.19	85.12	15.86	12.85
Jarque-Bera	131770.62	1053.30	682.02	5090.62	3966.98	132068.18	3236.76	1933.02
Probability	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Sum	-0.31	-0.20	0.08	1.58	2.54	0.01	2.99	2.98
Sum Sq. Dev.	0.02	0.04	0.01	1.23	2.28	0.01	2.82	3.10
Observations	470	470	470	470	470	470	470	470

Correlation Coefficients

Table 3 and Table 4 shows the correlation coefficients of all the variables. Prior to COVID, it was observed that the selected equity markets experience a positive relationship with the individual cryptocurrencies except for the negative correlation (-0.08) experienced between BSE and ADA. During the COVID period, only two relationships were reported as positive which were BSE and BNB (0.00) and JSE and ADA (0.02). Although, these were positive there was a decrease of 0.07 and 0.03 respectively. It can also be noted that before COVID, all cryptocurrencies are positively correlated with each other. Within the COVID period, there are four pairs that became negatively correlated: BTC and USDT (-0.25), ETH and USDT (-0.23), BNB and USDT (-0.21) and ADA and USDT (-0.20). USDT also known as Tether is a stablecoin. This implies that Tether is a centralized cryptocurrency which is pegged to the USD dollar and offers stability and is not subject to market volatility like other cryptocurrencies (Forbes, 2022). Thus, explaining its negative correlation with BTC, ETH, BNB and ADA.

Table 3. Correlations prior to the COVID period

Pre-COVID	BSE	JSE	TTSE	BTC	ETH	USDT	BNB	ADA
BSE	1	0.01	-0.03	0.02	0.00	0.01	0.07	-0.08
JSE	0.01	1	-0.04	0.12	0.08	0.04	0.09	0.05
TTSE	-0.03	-0.04	1	0.01	0.00	0.02	0.00	0.00
BTC	0.02	0.12	0.01	1	0.82	0.19	0.62	0.73
ETH	0.00	0.08	0.00	0.82	1	0.15	0.65	0.82
USDT	0.01	0.04	0.02	0.19	0.15	1	0.11	0.09
BNB	0.07	0.09	0.00	0.62	0.65	0.11	1	0.59
ADA	-0.08	0.05	0.00	0.73	0.82	0.09	0.59	1

Table 4. Correlations during the COVID period

COVID	BSE	JSE	TTSE	BTC	ETH	USDT	BNB	ADA
BSE	1	-0.13	0.03	-0.05	-0.03	-0.01	0.00	-0.04
JSE	-0.13	1	0.07	-0.02	-0.02	-0.02	-0.02	0.02
TTSE	0.03	0.07	1	-0.07	-0.05	-0.06	-0.04	-0.05
BTC	-0.05	-0.02	-0.07	1	0.81	-0.25	0.67	0.69
ETH	-0.03	-0.02	-0.05	0.81	1	-0.23	0.69	0.75
USDT	-0.01	-0.02	-0.06	-0.25	-0.23	1	-0.21	-0.20
BNB	0.00	-0.02	-0.04	0.67	0.69	-0.21	1	0.63
ADA	-0.04	0.02	-0.05	0.69	0.75	-0.20	0.63	1

Given that there are highly correlated variables in this study, the concern of multicollinearity arises. To address this concern, Variance Inflation Factors (VIF) are employed and the Centred VIF is considered. The centred VIF values were under 5 for both the pre-COVID and during COVID periods as seen in Table 5 which indicated that multicollinearity was not present.

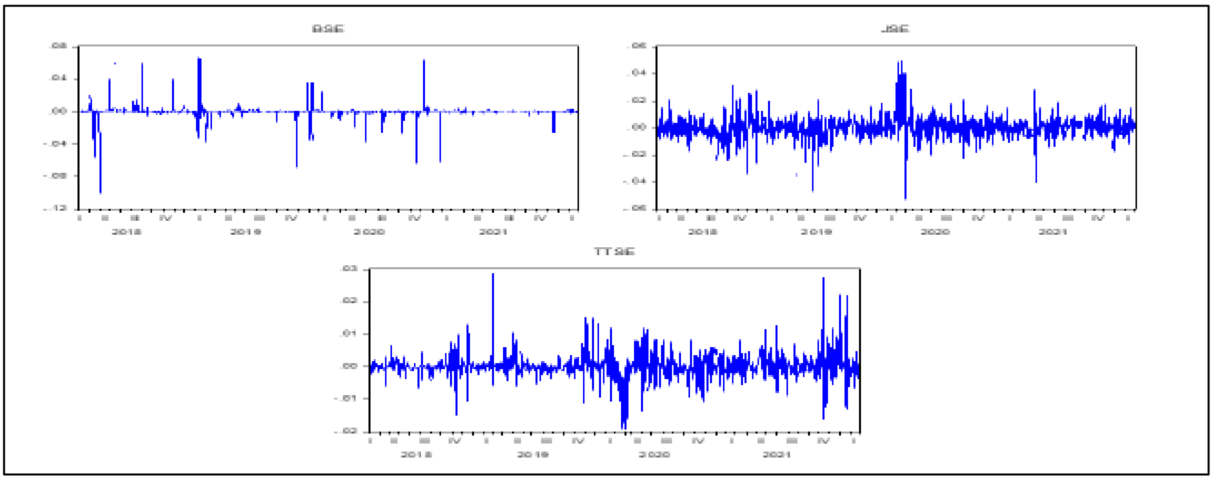
Table 5. Centred VIF values employed for multicollinearity testing

VIF	Pre-COVID	COVID
BTC	3.270888	3.018853
ETH	4.689984	3.490718
USDT	1.043261	1.108281
BNB	1.829024	1.919798
ADA	3.187826	1.942089

Residuals

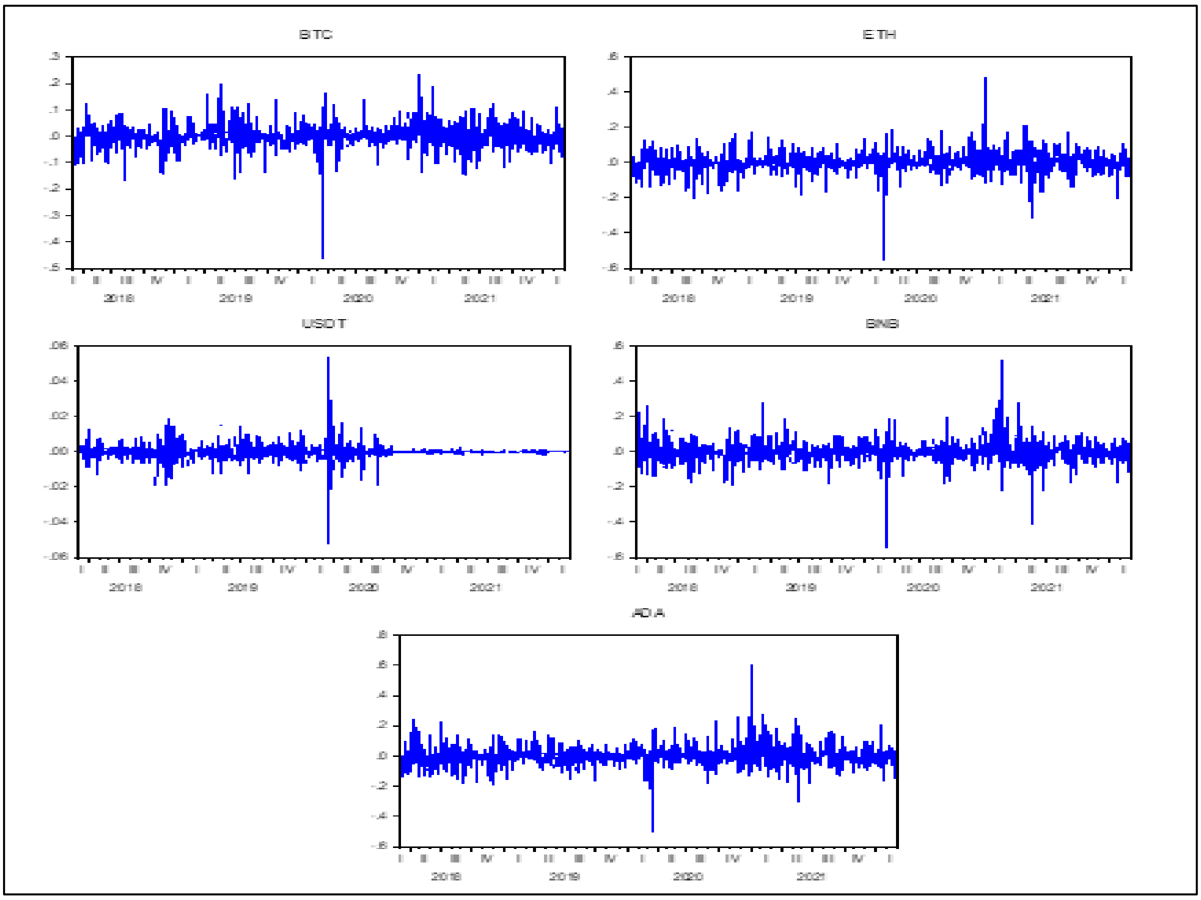
Residual volatility illustrations the extent in which market returns diverge from the index. From the selected Caribbean equity markets, it was observed that BSE has very low volatility in comparison to JSE and TTSE even amidst the COVID pandemic. Among the five cryptocurrencies, USDT was the least volatile especially after the onset of the pandemic which is expected due to its centralized nature and its peg to the USD dollar. On the contrary, the remaining four cryptocurrencies were highly volatile during the pandemic.

Graph 1. Selected Caribbean Equity Markets - Residual



Source: Authors calculation

Graph 2. Cryptocurrency Markets – Residual



Source: Authors calculation

Empirical Results

Unit Root Testing

To perform econometric modelling, it is required that the variables are first tested for stationarity. In this study, a VAR is being utilized and therefore, it is imperative that all variables are stationary. The following tests were employed to investigate the stationarity of each variable: the Augmented Dickey Fuller (ADF), Philips- Perron (PP) and Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test. The ADF test is superior to the Dickey Fuller (DF) because the ADF imposes p lags which addresses the issue of serial correlation among differenced variables. The PP and ADF use the same hypothesis, but serial correlation is not evaluated the same way for both tests. In the case of stationary tests, the ADF and PP tests are not as robust especially if its root is on the border of non-stationary. Therefore, the KPSS test is utilized. The KPSS test employs a null hypothesis in which the series follows a stationary process around a deterministic trend. The decision criterion for each test was made at the 5% level. The results are summarized in the Table 6 and Table 7 below. All markets prior to COVID were stationary at level, that is, I(0). However, JSE, BNB and ADA had to be differenced once to become stationary for the COVID period.

Table 6. Stationarity Test Results for pre-COVID period

Variable	ADF Test Statistic	PP Test Statistic	KPSS Test Statistic	Conclusion
BSE	-21.69333	-21.71261	0.076658	Stationary
JSE	-20.66565	-20.67179	0.141906	Stationary
TTSE	-24.40444	-24.49268	0.134260	Stationary
BTC	-20.88755	-20.91355	0.098935	Stationary
ETH	-20.56451	-20.88098	0.049218	Stationary
USDT	-19.71892	-37.06837	0.027037	Stationary
BNB	-21.27857	-21.27607	0.107788	Stationary
ADA	-20.21417	-20.37911	0.044205	Stationary
Critical Values for ADF: -3.977830 (1%), -3.419474 (5%), -3.132332 (10%) Critical Values for PP: -3.977830 (1%), -3.419474 (5%), -3.132332 (10%) Critical Values for KPSS: 0.216000 (1%), 0.146000 (5%), 0.119000 (10%) The conclusion was determined at 5%				

Table 7. Stationarity Test Results for COVID period

Variable	ADF Test Statistic	PP Test Statistic	KPSS Test Statistic	Conclusion
BSE	-21.86259	-21.86303	0.027452	Stationary
JSE	-20.96957	-21.25974	0.186765	Not Stationary
dJSE	-18.41011	-135.9672	0.056622	Stationary
TTSE	-24.30410	-25.15055	0.085700	Stationary
BTC	-22.65565	-22.65565	0.107914	Stationary
ETH	-24.01597	-23.93223	0.101949	Stationary
USDT	-13.49652	-185.7640	0.060993	Stationary
BNB	-7.443358	-21.59706	0.188104	Not Stationary
dBNB	-15.15004	-149.5060	0.046295	Stationary
ADA	-23.75574	-23.75140	0.149965	Not Stationary
dADA	-13.68788	-190.4759	0.052379	Stationary
Critical Values for ADF: -3.977745 (1%), -3.419432 (5%), -3.132308 (10%) Critical Values for PP: -3.977745 (1%), -3.419432 (5%), -3.132308 (10%) Critical Values for KPSS: 0.216000 (1%), 0.146000 (5%), 0.119000 (10%) The conclusion was determined at 5%				

The VAR Lag Order Selection Criteria Test was used to determine the optimal lag length for each iteration of the model. According to the results obtained for the pre-COVID period, the optimal lag length is 3 and 0 based on the Akaike Information Criterion (AIC) and Schwarz Information Criterion (SC) respectively shown in Table 8. As such it was necessary to rely on the serial correlation test to aid in determining the optimal lag length. This test indicated that an optimal lag length of 3 is sufficient as no serial correlation exists as seen in Table 9. The VAR Lag Length Test results were not the same for each stock market during the COVID period considered. The lag lengths for BSE, JSE and TTSE were decided to be 9, 10 and 9 respectively because serial correlation was not present as shown in Table 10 and Table 11.

Table 8. VAR Lag Length Test of BSE, JSE and TTSE for pre COVID period

VAR Lag Order Selection Criteria for BSE

Lag	LogL	LR	FPE	AIC	SC	HQ
0	6674.592	NA	1.03e-20	-28.99388	-28.93999*	-28.97266*
1	6718.390	86.26141	9.97e-21	-29.02778	-28.65058	-28.87925
2	6764.839	90.27277	9.52e-21	-29.07321	-28.37270	-28.79736
3	6805.604	78.16268*	9.33e-21*	-29.09393*	-28.07010	-28.69077

VAR Lag Order Selection Criteria for JSE

Lag	LogL	LR	FPE	AIC	SC	HQ
0	6751.208	NA	7.39e-21	-29.32699	-29.27311*	-29.30577*
1	6799.121	94.36758	7.02e-21	-29.37879	-29.00159	-29.23025
2	6846.970	92.99402	6.66e-21	-29.43030	-28.72979	-29.15446
3	6889.437	81.42624*	6.48e-21*	-29.45842*	-28.43460	-29.05526

VAR Lag Order Selection Criteria for TTSE

Lag	LogL	LR	FPE	AIC	SC	HQ
0	7208.145	NA	1.01e-21	-31.31368	-31.25979*	-31.29246*
1	7254.789	91.86858	9.68e-22	-31.35995	-30.98276	-31.21142
2	7296.139	80.36260	9.45e-22	-31.38321	-30.68270	-31.10737
3	7350.496	104.2234*	8.73e-22*	-31.46303*	-30.43920	-31.05987

Table 9. VAR Lag Length Test of BSE, JSE and TTSE for COVID period

VAR Lag Order Selection Criteria for BSE						
Lag	LogL	LR	FPE	AIC	SC	HQ
0	6280.066	NA	6.08e-20	-27.21937	-27.16558	-27.19819
1	6541.006	513.9555	2.29e-20	-28.19525	-27.81867*	-28.04698
2	6642.532	197.3262	1.72e-20	-28.47953	-27.78017	-28.20416
3	6722.685	153.6982	1.42e-20	-28.67108	-27.64894	-28.26862
4	6813.933	172.6007	1.12e-20	-28.91077	-27.56585	-28.38122*
5	6871.227	106.8822	1.02e-20	-29.00315	-27.33545	-28.34651
6	6919.046	87.96150	9.72e-21*	-29.05443*	-27.06394	-28.27069
7	6952.480	60.63053	9.85e-21	-29.04330	-26.73003	-28.13246
8	6988.733	64.79957*	9.85e-21	-29.04439	-26.40834	-28.00647

VAR Lag Order Selection Criteria for JSE						
Lag	LogL	LR	FPE	AIC	SC	HQ
0	6109.823	NA	1.27e-19	-26.48079	-26.42700	-26.45961
1	6383.930	539.8903	4.53e-20	-27.51380	-27.13722*	-27.36552
2	6488.132	202.5264	3.37e-20	-27.80968	-27.11032	-27.53431
3	6574.237	165.1138	2.71e-20	-28.02706	-27.00492	-27.62460
4	6661.240	164.5691	2.17e-20	-28.24833	-26.90341	-27.71878
5	6728.730	125.9029	1.90e-20	-28.38495	-26.71724	-27.72830*
6	6789.317	111.4485	1.71e-20	-28.49161	-26.50113	-27.70787
7	6828.581	71.20364	1.69e-20	-28.50578	-26.19251	-27.59494
8	6868.123	70.67850*	1.66e-20*	-28.52114*	-25.88509	-27.48322

VAR Lag Order Selection Criteria for TTSE						
Lag	LogL	LR	FPE	AIC	SC	HQ
0	6391.994	NA	3.74e-20	-27.70496	-27.65117	-27.68378
1	6660.309	528.4811	1.37e-20	-28.71284	-28.33626	-28.56456
2	6771.909	216.9063	9.84e-21	-29.04082	-28.34146*	-28.76545
3	6853.365	156.1975	8.08e-21	-29.23803	-28.21588	-28.83556
4	6947.415	177.8993	6.28e-21	-29.48987	-28.14495	-28.96032
5	7013.386	123.0704	5.52e-21	-29.61990	-27.95219	-28.96325*
6	7068.280	100.9750	5.09e-21*	-29.70186*	-27.71138	-28.91812
7	7099.243	56.14977	5.21e-21	-29.68001	-27.36674	-28.76918
8	7136.837	67.19619*	5.18e-21	-29.68693	-27.05088	-28.64900

Figure 1. AR Roots Graph for BSE, JSE and TTSE for pre-COVID period

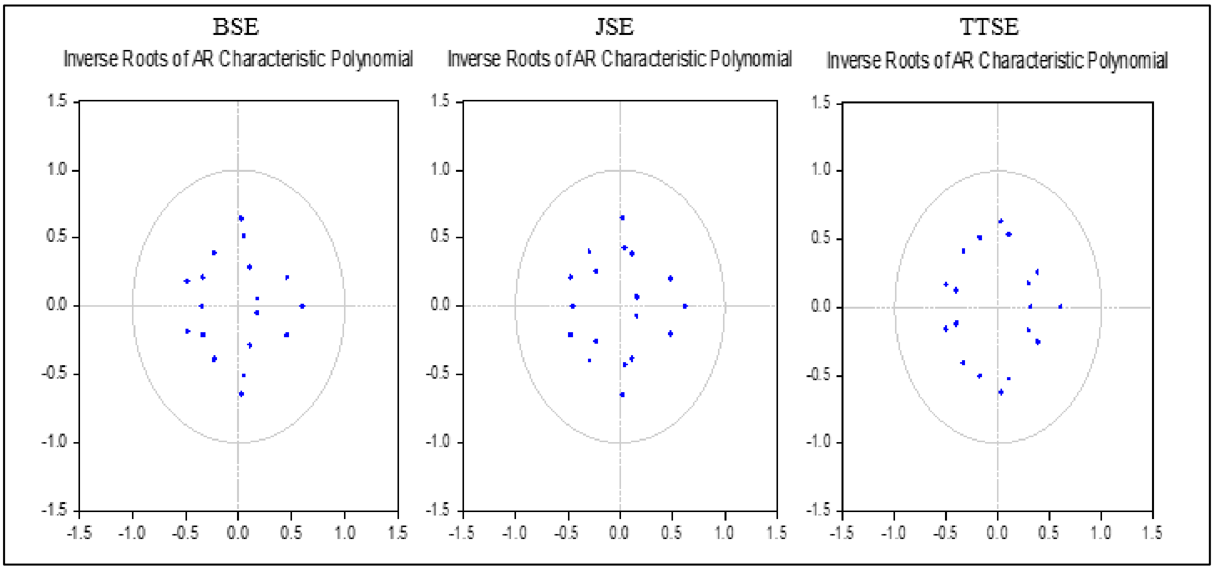


Figure 2. AR Roots Graph for BSE, JSE and TTSE for COVID period

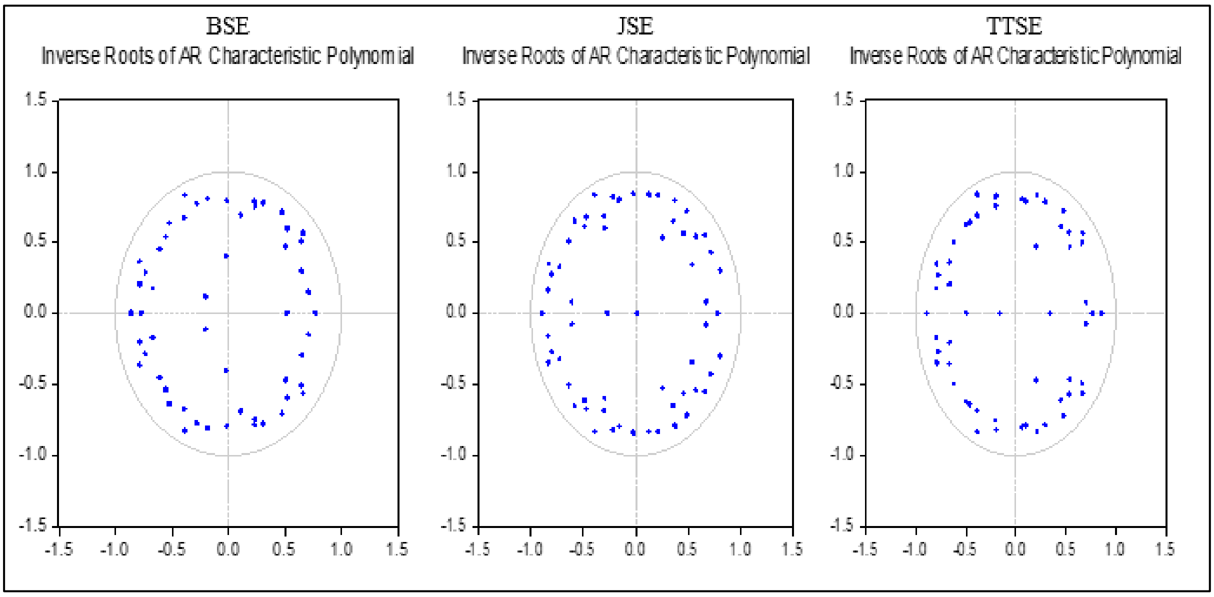


Figure 1 and Figure 2 illustrates the AR roots graph for each of the respective VAR models that were estimated with their respective lag length specification. Figure 1 and Figure 2 reveal that each of the estimated models are stationary and stable due to the roots being within the circle boundary shown. This implies that the impulse response errors of each VAR will be valid for both the pre-COVID and COVID periods. Table 9 and Table 10 shows the LM serial Correlation test for BSE, JSE and TTSE which has lags in each case. The p-values for each of the respective models up to the lag length determined by the lag length criteria test indicated that there will be no serial correlation at these chosen lags.

Table 10. Serial Correlation Test Results for BSE, JSE and TTSE for pre-COVID period

VAR Residual Serial Correlation LM Tests for BSE		
Lags	LM-Stat	Prob
1	51.35128	0.0467
2	32.81697	0.6208
3	37.44020	0.4029

VAR Residual Serial Correlation LM Tests for JSE		
Lags	LM-Stat	Prob
1	40.79747	0.2677
2	32.59024	0.6316
3	46.06690	0.1214

VAR Residual Serial Correlation LM Tests for TTSE		
Lags	LM-Stat	Prob
1	45.12639	0.1416
2	23.79922	0.9408
3	38.66119	0.3503

Table 11. Serial Correlation Test Results for BSE, JSE and TTSE for COVID period

VAR Residual Serial Correlation LM Tests for BSE		
Lags	LM-Stat	Prob
1	97.82233	0.0000
2	139.4249	0.0000
3	61.86896	0.0047
4	85.73584	0.0000
5	94.70512	0.0000
6	78.39753	0.0001
7	64.33588	0.0025
8	62.90451	0.0036
9	42.71003	0.2050

VAR Residual Serial Correlation LM Tests for JSE		
Lags	LM-Stat	Prob
1	120.6001	0.0000
2	59.99720	0.0073
3	78.27312	0.0001
4	87.89984	0.0000
5	70.98204	0.0004
6	51.89977	0.0419
7	73.63606	0.0002
8	60.80564	0.0060
9	48.41016	0.0810
10	48.08752	0.0858

VAR Residual Serial Correlation LM Tests for TTSE		
Lags	LM-Stat	Prob
1	122.5047	0.0000
2	162.5802	0.0000
3	74.20886	0.0002
4	93.86584	0.0000
5	84.42621	0.0000
6	76.35564	0.0001
7	70.39760	0.0005
8	69.71336	0.0006
9	36.50114	0.4454

Table 12. Granger Causality Results for BSE, JSE and TTSE for pre-COVID period

VAR Granger Causality/Block Exogeneity Wald Tests			
Dependent variable: BSE			
Excluded	Chi-sq	df	Prob.
BTC	1.171882	3	0.7598
ETH	0.367503	3	0.9469
USDT	3.080823	3	0.3793
BNB	0.543950	3	0.9091
ADA	1.032752	3	0.7933
All	8.124602	15	0.9187

VAR Granger Causality/Block Exogeneity Wald Tests			
Dependent variable: JSE			
Excluded	Chi-sq	df	Prob.
BTC	5.117721	3	0.1634
ETH	6.023594	3	0.1105
USDT	3.321234	3	0.3447
BNB	2.488482	3	0.4774
ADA	2.815345	3	0.4210
All	18.11942	15	0.2564

VAR Granger Causality/Block Exogeneity Wald Tests			
Dependent variable: TTSE			
Excluded	Chi-sq	df	Prob.
BTC	0.514807	3	0.9156
ETH	4.637466	3	0.2004
USDT	4.184337	3	0.2422
BNB	0.096864	3	0.9922
ADA	1.608096	3	0.6576
All	10.53619	15	0.7847

Table 13. Granger Causality Results for BSE, JSE and TTSE for COVID period

VAR Granger Causality/Block Exogeneity Wald Tests			
Dependent variable: BSE			
Excluded	Chi-sq	df	Prob.
BTC	12.72072	9	0.1757
ETH	14.36266	9	0.1100
USDT	6.277787	9	0.7118
DBNB	3.933237	9	0.9158
DADA	12.44802	9	0.1892
All	41.11282	45	0.6373

VAR Granger Causality/Block Exogeneity Wald Tests			
Dependent variable: JSE			
Excluded	Chi-sq	df	Prob.
BTC	17.69683	10	0.0603
ETH	13.19521	10	0.2130
USDT	57.44767	10	0.0000
DBNB	6.430839	10	0.7779
DADA	2.470840	10	0.9913
All	119.8338	50	0.0000

VAR Granger Causality/Block Exogeneity Wald Tests			
Dependent variable: TTSE			
Excluded	Chi-sq	df	Prob.
BTC	4.707198	9	0.8590
ETH	12.68990	9	0.1771
USDT	23.09818	9	0.0060
DBNB	6.929398	9	0.6445
DADA	23.99659	9	0.0043
All	75.44649	45	0.0030

Table 13 shows the results of the Granger Causality Tests between the individual stock markets and the respective cryptocurrencies prior to COVID. Granger Causality tests are used to determine whether there are any short run relationships between the chosen variables. According to Granger (1969), granger causality can be illustrated in the following manner: “x is a Granger cause of y (denoted as x → y) if present y can be predicted with better accuracy by using past values of x rather than by not doing so, other information being identical (Charemza and Deadman, 1997). It is established that none of the cryptocurrency’s granger cause the selected stock markets. Therefore, it can be concluded that past returns of the five selected cryptocurrencies do not influence the present returns of the three selected stock markets. However, during COVID there was granger causality found observed between the following pairs: JSE and USDT, TTSE and USDT and TTSE and DADA shown in Table 12.

A VAR model was constructed considering these diagnostics and the spillover effects were analyzed with the use of impulse response and variance decomposition. The spillover effects can be segmented into endogenous and exogenous shocks. The endogenous shock or idiosyncratic shocks are direct linkages, in this case it is a shock from either BSE, JSE or TTSE depending on the respective model.

Table 14. Variance Decomposition for BSE, JSE and TTSE for pre-COVID period

Variance Decomposition of BSE							
Period	S.E.	BTC	ETH	USDT	BNB	ADA	BSE
1	0.010269	0.081090	0.061414	0.058732	0.771225	1.890823	97.13672
2	0.010282	0.118581	0.061679	0.085444	0.804576	2.040253	96.88947
3	0.010332	0.761955	0.063474	0.181297	0.905043	2.091982	95.99625
4	0.010358	0.906530	0.072989	0.501819	0.901307	2.089241	95.52811
5	0.010363	0.932229	0.073084	0.556656	0.900726	2.087161	95.45014
6	0.010365	0.932500	0.076733	0.575933	0.902514	2.086628	95.42569
7	0.010365	0.933025	0.076796	0.576119	0.902620	2.086722	95.42472
8	0.010366	0.933799	0.076957	0.589119	0.902935	2.086661	95.41053
9	0.010366	0.934174	0.076957	0.589451	0.903083	2.086808	95.40953
10	0.010366	0.934341	0.076974	0.590877	0.903094	2.086772	95.40794
Cholesky Ordering: BTC ETH USDT BNB ADA BSE							

Variance Decomposition of JSE							
Period	S.E.	BTC	ETH	USDT	BNB	ADA	JSE
1	0.008564	1.359991	0.068527	0.236691	0.036109	0.145717	98.15297
2	0.008637	1.364394	0.477388	0.766811	0.036089	0.704055	96.65126
3	0.008692	1.989535	0.580593	0.780150	0.426569	0.762295	95.46086
4	0.008739	2.141606	1.173414	0.914424	0.472609	0.758790	94.53916
5	0.008745	2.203736	1.202261	0.934568	0.474257	0.781858	94.40332
6	0.008747	2.218186	1.202632	0.936650	0.474136	0.785193	94.38320
7	0.008748	2.230812	1.205496	0.936361	0.477402	0.790542	94.35939
8	0.008748	2.231474	1.206855	0.936339	0.477554	0.790892	94.35689
9	0.008748	2.231449	1.207546	0.936686	0.477927	0.790881	94.35551
10	0.008748	2.231890	1.207552	0.936731	0.478011	0.790876	94.35494
Cholesky Ordering: BTC ETH USDT BNB ADA JSE							

Variance Decomposition of TTSE							
Period	S.E.	BTC	ETH	USDT	BNB	ADA	TTSE
1	0.003141	0.023704	0.054844	0.250979	0.000548	0.000949	99.66898
2	0.003168	0.030625	0.088746	0.403200	0.001775	0.037626	99.43803
3	0.003177	0.044561	0.173772	0.620662	0.010125	0.112256	99.03862
4	0.003197	0.261961	0.768004	0.718990	0.012600	0.342940	97.89550
5	0.003202	0.354112	0.770862	0.964898	0.012597	0.345630	97.55190
6	0.003203	0.354843	0.770619	0.966092	0.019267	0.362669	97.52651
7	0.003205	0.418444	0.770267	1.005764	0.019528	0.369864	97.41613
8	0.003205	0.418472	0.770773	1.006417	0.020835	0.369855	97.41365
9	0.003205	0.420765	0.770785	1.018521	0.021794	0.370195	97.39794
10	0.003205	0.421520	0.770779	1.018592	0.022606	0.370215	97.39629
Cholesky Ordering: BTC ETH USDT BNB ADA TTSE							

Table 15. Variance Decomposition for BSE, JSE and TTSE for COVID period

Variance Decomposition of BSE							
Period	S.E.	BTC	ETH	USDT	DBNB	DADA	BSE
1	0.006089	0.572102	0.021184	0.212060	0.005313	0.029315	99.16003
2	0.006136	0.806978	0.395376	0.784599	0.025602	0.331963	97.65548
3	0.006163	0.954239	0.503487	0.882235	0.028752	0.333882	97.29740
4	0.006175	1.030876	0.617201	0.925093	0.031196	0.480769	96.91486
5	0.006200	1.274319	0.840061	0.946176	0.253443	0.530676	96.15533
6	0.006209	1.276315	0.869702	1.084438	0.252818	0.561623	95.95510
7	0.006245	1.279313	1.723491	1.103159	0.399433	0.638917	94.85569
8	0.006309	1.331734	2.637472	1.081243	0.516053	1.443441	92.99006
9	0.006313	1.377286	2.649594	1.090425	0.529707	1.448360	92.90463
10	0.006370	1.397252	3.558390	1.096968	0.520668	2.159650	91.26707
Cholesky Ordering: BTC ETH USDT DBNB DADA BSE							

Variance Decomposition of JSE							
Period	S.E.	BTC	ETH	USDT	DBNB	DADA	JSE
1	0.007640	0.190298	0.258607	0.083745	0.207624	0.372240	98.88749
2	0.007715	0.635290	0.360906	0.586851	0.285768	0.365748	97.76544
3	0.007728	0.652889	0.527041	0.596639	0.324814	0.365493	97.53312
4	0.007923	1.064273	1.984019	3.172314	0.408714	0.368902	93.00178
5	0.007955	1.093438	2.389558	3.147931	0.541857	0.521412	92.30580
6	0.008016	2.154841	2.642597	3.176901	0.540312	0.514196	90.97115
7	0.008051	2.349080	2.783704	3.474384	0.668401	0.514174	90.21026
8	0.008156	3.654741	2.759524	3.402945	0.869879	0.565268	88.74764
9	0.008243	3.612928	3.271798	3.793429	1.374980	0.579233	87.36763
10	0.008327	3.628782	3.398814	5.355961	1.348622	0.608603	85.65922
Cholesky Ordering: BTC ETH USDT DBNB DADA JSE							

Variance Decomposition of TTSE							
Period	S.E.	BTC	ETH	USDT	DBNB	DADA	TTSE
1	0.004376	0.284746	0.004815	0.124602	0.020337	0.008521	99.55698
2	0.004487	0.442605	0.416671	1.746300	0.161928	0.729568	96.50293
3	0.004557	0.451504	0.673157	2.265439	0.655456	0.984637	94.96981
4	0.004632	0.461475	0.916884	2.820118	0.635681	3.236191	91.92965
5	0.004693	0.468285	0.916183	2.826753	0.722801	3.736750	91.32923
6	0.004758	1.225068	1.015352	3.038962	0.758292	3.649167	90.31316
7	0.004783	1.498403	1.307740	3.119084	0.822722	3.632158	89.61989
8	0.004831	1.586453	1.599537	3.078422	0.901517	4.700742	88.13333
9	0.004881	1.648789	1.566683	3.491847	0.945622	4.892716	87.45434
10	0.004909	2.021737	1.609799	3.516359	0.942811	4.869535	87.03976
Cholesky Ordering: BTC ETH USDT DBNB DADA TTSE							

For this study, the short run is considered as the third period and in the long run as the tenth period. Prior to COVID-19, similar results were observed for the three selected stock exchanges. In the short run, the idiosyncratic shocks accounted for 96%, 95.46% and 99.04% for BSE, JSE and TTSE respectively. Whilst in the long run, marginal decreases were observed to 95.41%, 94.36% and 97.40%. BTC, ETH, USDT, BNB and ADA contributed 0.93%, 0.08%, 0.60%, 0.90% and 2.09% respectively to return variance of BSE for the long run. BTC, ETH, USDT, BNB and ADA contributed 2.23%, 1.21%, 0.94%, 0.48% and 0.80% respectively to the return variance of JSE. BTC, ETH, USDT, BNB and ADA contributed 0.42%, 0.77%, 1.02%, 0.02% and 0.37% respectively to the return variance of TTSE in the long run. Cumulatively, the five selected cryptocurrencies accounted for approximately 4.60%, 5.66% and 2.60% of the return variance for BSE, JSE and TTSE respectively.

During COVID-19, similar results were observed for the three selected stock exchanges. In the short run, the idiosyncratic shocks accounted for 97.30%, 97.53% and 95% for BSE, JSE and TTSE respectively. Whilst in the long run declines were observed to 91.27%, 85.66% and 87.04%. The rate of decline between the short run and long run is more substantial during the COVID-19 period than prior to COVID. BTC, ETH, USDT, BNB and ADA contributed 01.40%, 3.56%, 1.10%, 0.52% and 2.16% respectively to return variance of BSE for the long run. BTC, ETH, USDT, BNB and ADA contributed 3.63%, 3.40%, 5.36%, 1.35% and 0.61% respectively to the return variance of JSE. BTC, ETH, USDT, BNB and ADA contributed 2.02%, 1.61%, 3.52%, 0.94% and 4.87% respectively to the return variance of TTSE in the long run. Cumulatively, the five selected cryptocurrencies accounted for approximately 8.44%, 14.35% and 12.66% of the return variance for BSE, JSE and TTSE respectively.

Table 16. Impulse Response for BSE, JSE and TTSE for pre-COVID period

Response of BSE						
Period	BTC	ETH	USDT	BNB	ADA	BSE
1	0.000292	-0.000254	0.000249	0.000902	-0.001412	0.010121
2	0.000200	-2.12E-05	0.000169	-0.000193	-0.000404	-7.84E-05
3	-0.000829	-5.05E-05	0.000321	0.000340	-0.000276	0.000195
4	0.000399	-0.000103	0.000587	-2.94E-05	9.12E-05	-0.000121
5	-0.000169	-1.37E-05	-0.000244	2.07E-05	1.45E-05	0.000167
6	-2.37E-05	-6.28E-05	-0.000144	4.67E-05	-5.83E-06	3.86E-05
7	-2.40E-05	8.29E-06	1.44E-05	-1.12E-05	-1.14E-05	-1.63E-05
8	3.13E-05	-1.36E-05	0.000119	2.20E-05	-1.65E-05	1.12E-05
9	-2.03E-05	8.47E-07	-1.91E-05	1.30E-05	1.35E-05	2.95E-06
10	-1.40E-05	-4.49E-06	-3.93E-05	-5.31E-06	-2.02E-07	6.21E-06
Cholesky Ordering: BTC ETH USDT BNB ADA BSE						

Response of JSE						
Period	BTC	ETH	USDT	BNB	ADA	JSE
1	0.000999	-0.000224	0.000417	0.000163	-0.000327	0.008484
2	-0.000143	0.000553	0.000631	2.10E-05	-0.000647	0.000339
3	-0.000697	-0.000287	0.000132	-0.000543	0.000225	0.000156
4	0.000364	-0.000676	-0.000330	-0.000197	5.95E-05	0.000272
5	0.000223	-0.000153	0.000128	4.22E-05	-0.000136	9.97E-06
6	-0.000108	-2.38E-05	4.26E-05	4.23E-06	-5.23E-05	8.16E-05
7	-0.000101	-4.98E-05	1.09E-06	-5.11E-05	6.54E-05	6.42E-05
8	-2.35E-05	-3.26E-05	-1.50E-06	-1.12E-05	1.69E-05	5.05E-06
9	-2.41E-06	-2.33E-05	1.66E-05	1.71E-05	-4.17E-07	4.35E-06
10	-1.87E-05	-3.36E-06	-6.26E-06	8.14E-06	-6.03E-07	5.90E-06
Cholesky Ordering: BTC ETH USDT BNB ADA JSE						

Response of TTSE						
Period	BTC	ETH	USDT	BNB	ADA	TTSE
1	4.84E-05	-7.36E-05	0.000157	-7.35E-06	-9.68E-06	0.003136
2	2.71E-05	5.91E-05	0.000125	1.11E-05	-6.07E-05	-0.000380
3	-3.77E-05	-9.29E-05	0.000149	-2.90E-05	8.69E-05	-0.000126
4	0.000149	0.000247	0.000104	-1.63E-05	-0.000154	8.79E-05
5	-9.77E-05	2.39E-05	-0.000160	-2.06E-06	2.00E-05	-9.57E-06
6	-9.33E-06	1.15E-06	-1.25E-05	-2.62E-05	4.19E-05	-2.67E-05
7	8.11E-05	8.33E-06	6.49E-05	-5.42E-06	-2.81E-05	4.50E-05
8	2.01E-06	7.35E-06	8.35E-06	1.16E-05	1.59E-07	-5.32E-07
9	-1.56E-05	3.80E-06	-3.55E-05	-9.95E-06	6.43E-06	-7.70E-06
10	8.86E-06	1.01E-06	3.07E-06	-9.13E-06	-1.68E-06	5.66E-06
Cholesky Ordering: BTC ETH USDT BNB ADA TTSE						

Table 17. Impulse Response for BSE, JSE and TTSE for COVID period

Response of BSE						
Period	BTC	ETH	USDT	DBNB	DADA	BSE
1	-0.000461	8.86E-05	-0.000280	-4.44E-05	-0.000104	0.006064
2	0.000303	0.000376	-0.000466	-8.76E-05	-0.000338	-6.80E-05
3	0.000242	-0.000206	-0.000199	3.58E-05	4.24E-05	0.000423
4	-0.000175	-0.000210	-0.000133	-3.12E-05	0.000238	6.16E-05
5	0.000311	0.000296	0.000105	-0.000292	-0.000144	9.02E-05
6	-4.62E-05	-0.000111	-0.000233	5.62E-06	-0.000112	0.000162
7	-8.35E-05	-0.000580	-0.000111	0.000242	0.000181	8.95E-05
8	0.000176	-0.000614	-7.71E-06	-0.000223	-0.000570	-0.000112
9	-0.000137	-7.92E-05	-6.52E-05	7.57E-05	5.24E-05	-0.000130
10	-0.000135	0.000623	0.000103	1.37E-05	0.000547	-0.000108
Cholesky Ordering: BTC ETH USDT DBNB DADA BSE						

Response of JSE						
Period	BTC	ETH	USDT	DBNB	DADA	JSE
1	-0.000333	-0.000389	0.000221	-0.000348	0.000466	0.007598
2	-0.000517	0.000253	0.000548	0.000221	2.04E-05	-0.000685
3	0.000109	-0.000316	8.38E-05	0.000155	2.41E-05	0.000239
4	-0.000527	0.000965	0.001279	-0.000250	-0.000115	0.000355
5	0.000155	-0.000517	2.85E-05	0.000294	0.000314	-0.000189
6	0.000832	-0.000431	0.000222	-6.54E-05	2.08E-05	0.000199
7	0.000371	0.000326	0.000459	0.000293	-5.33E-05	-0.000113
8	0.000953	0.000177	-0.000108	0.000381	-0.000207	-0.000750
9	-0.000155	0.000623	-0.000561	-0.000596	0.000133	-0.000581
10	0.000247	-0.000365	-0.001066	-2.74E-05	-0.000168	-0.000156
Cholesky Ordering: BTC ETH USDT DBNB DADA JSE						

Response of TTSE						
Period	BTC	ETH	USDT	DBNB	DADA	TTSE
1	-0.000234	3.04E-05	-0.000154	-6.24E-05	-4.04E-05	0.004366
2	0.000186	-0.000288	0.000572	0.000169	-0.000381	-0.000603
3	-6.83E-05	0.000236	-0.000345	-0.000322	0.000240	0.000545
4	7.25E-05	0.000239	0.000367	-1.65E-05	-0.000700	-4.15E-05
5	-6.42E-05	7.11E-05	-0.000132	0.000151	0.000359	0.000625
6	0.000417	0.000167	0.000256	0.000112	5.50E-05	0.000573
7	0.000256	0.000263	0.000160	-0.000129	7.03E-05	0.000245
8	0.000165	0.000272	-6.89E-05	-0.000149	-0.000516	0.000249
9	0.000150	-1.46E-06	-0.000337	0.000122	0.000262	0.000519
10	0.000307	0.000121	0.000125	-4.40E-05	-8.90E-05	0.000376
Cholesky Ordering: BTC ETH USDT DBNB DADA TTSE						

For both the short run and long run of the pre-COVID and COVID period, the results of the impulse response indicated that at two decimal places, the value of the spillover effect is insignificant. Therefore, it can be concluded that the selected stock exchanges are not impacted by the returns of the top five cryptocurrencies as the impulse responses were trivial shown in Table 16, Table 17, Figure 3, and Figure 4.

Figure 3. Impulse Response Graphs for BSE, JSE and TTSE for the pre-COVID period

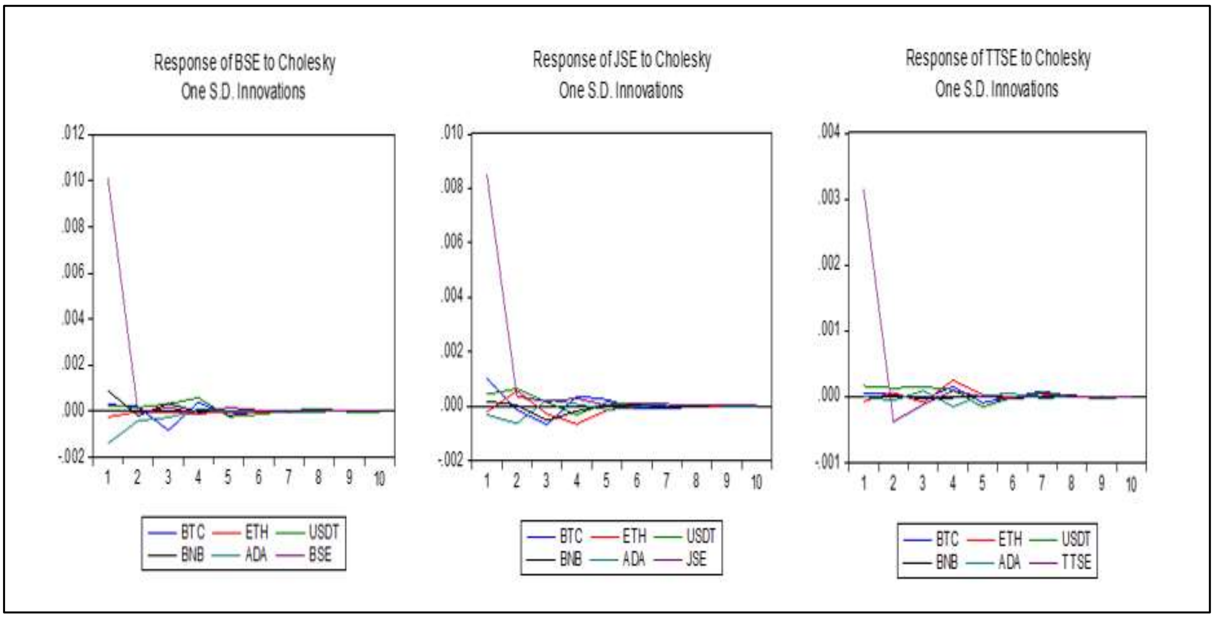
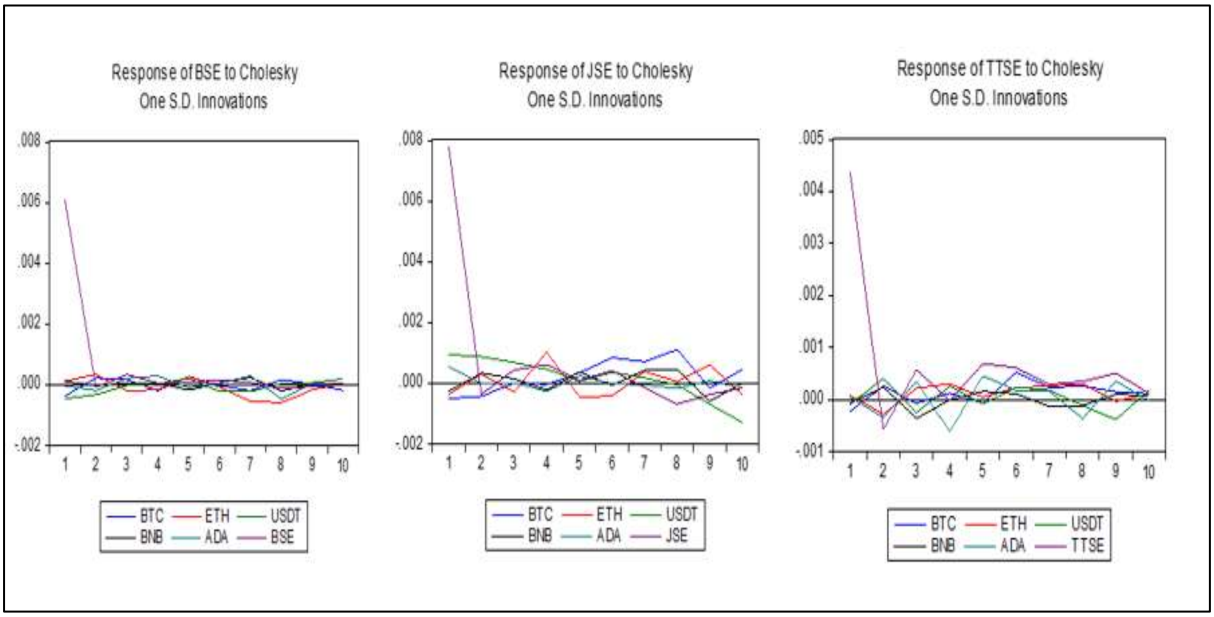


Figure 4. Impulse Response Graphs for BSE, JSE and TTSE for the COVID period



VaR Results and Interpretation

Table 18 and 19 shows the Value at Risk (VaR) and Conditional VaR (CVaR) also known as the expected shortfall (ES) for the selected stock markets and five selected cryptocurrencies over two subperiods using the historical approach, parametric approach, and modified approach at three confidence intervals. Note: The first, second and third numbers represents the value at the 10%, 5% and 1% confidence intervals respectively.

Table 18. VaR and CVaR pre-COVID results for three approaches at 1%, 5% and 10%

Pre-COVID	Historical %		Parametric %		Modified%	
	VaR	**CVaR**	**VaR**	**CVaR**	**VaR**	**CVaR**
BSE	0.13	1.31	1.30	1.78	1.14	3.92
	0.40	2.52	1.66	2.09	1.33	8.00
	0.04	6.63	2.35	2.70	11.58	21.30
JSE	0.79	1.36	0.99	1.39	0.72	1.33
	1.22	1.77	1.30	1.66	1.09	1.78
	2.16	2.69	1.88	2.17	2.17	3.04
TTSE	0.20	0.46	0.37	0.52	0.07	0.39
	0.37	0.65	0.49	0.62	0.14	0.78
	0.90	1.16	0.70	0.81	1.11	2.10
BTC	5.01	8.45	5.70	7.79	4.78	8.36
	7.85	10.96	7.30	9.14	7.03	10.96
	13.94	15.39	10.31	11.80	13.21	17.91
ETH	7.10	11.45	7.48	10.14	7.00	11.05
	11.19	14.70	9.52	11.86	9.73	13.89
	16.07	18.33	13.34	15.25	16.35	20.85
USDT	0.49	0.79	0.59	0.80	0.48	0.84
	0.65	1.04	0.75	0.94	0.70	1.10
	1.30	1.71	1.06	1.22	1.33	1.81
BNB	6.84	10.51	7.56	10.39	6.22	10.03
	9.29	13.08	9.73	12.24	8.67	12.77
	15.18	17.85	13.82	15.85	15.12	19.96
ADA	8.26	12.28	8.61	11.65	7.98	11.69
	12.28	14.95	10.94	13.63	10.56	14.25
	16.17	17.99	15.32	17.49	16.45	20.29

Table 19. VaR and CVaR COVID results for three approaches at 1%, 5% and 10%

COVID	Historical %		Parametric %		Modified %	
	VaR	**CVaR**	**VaR**	**CVaR**	**VaR**	**CVaR**
	0.18	0.89	0.83	1.11	2.07	3.39
BSE	0.30	1.56	1.05	1.30	0.51	7.85
	2.62	4.78	1.45	1.65	11.75	22.63
	0.91	1.78	1.22	1.66	0.79	2.12
JSE	1.44	2.47	1.56	1.94	1.54	3.13
	2.99	4.35	2.19	2.50	4.01	6.12
	0.48	0.85	0.59	0.81	0.37	0.86
TTSE	0.73	1.11	0.76	0.96	0.65	1.23
	1.57	1.74	1.08	1.24	1.56	2.35
	4.65	9.03	6.23	8.66	16.5	14.09
BTC	7.00	12.31	8.09	10.23	8.29	23.81
	13.72	22.42	11.58	13.32	32.32	53.74
	6.64	11.88	8.40	11.70	1.67	17.60
ETH	9.53	16.10	10.94	13.85	9.95	30.15
	18.70	32.31	15.69	18.05	41.11	69.55
	0.17	0.55	0.58	0.80	2.18	2.49
USDT	0.27	0.90	0.75	0.94	0.08	6.34
	1.49	2.72	1.06	1.21	9.71	19.46
	6.12	12.70	9.31	12.98	2.02	17.81
BNB	9.44	18.00	12.13	15.37	10.16	30.29
	21.75	35.40	17.41	20.04	41.18	69.73
	7.68	12.45	9.78	13.62	3.55	15.13
ADA	9.72	16.39	12.73	16.13	9.57	24.25
	18.40	30.11	18.27	21.02	32.18	52.99

By way of explanation, the results in both tables can be explained as follows: Under the historical approach, for JSE at the 10% confidence interval, the VaR is 0.79% which indicates to the investor that there is 90% confidence that a loss greater than 0.79% would not be incurred. The corresponding CVaR is 1.36% implies that the average of the losses incurred once the 90% VaR (0.79%) has been exceeded the is 1.36%. Similarly, at the 5% confidence interval, the VaR is 1.22% which indicates to the investor that there is 95% confidence that a loss greater than 1.22% would not be incurred. The corresponding CVaR is 1.77% implies that the average of the losses incurred once the 95% VaR (1.22%) has been exceeded the is 1.77%. Likewise, at the 1% confidence interval, the VaR is 2.16% which indicates to the investor that there is 99% confidence that a loss greater than 2.16% would not be incurred. The corresponding CVaR is 2.69% implies that the average of the losses incurred once the 99% VaR (2.16%) has been exceeded the is 2.69%. The same interpretation can be applied for both the parametric and modified approaches.

Value at Risk (VaR) is a popular financial tool used in assessing the risk of a stock or portfolio. According to the literature as the confidence interval decreases the VaR and expected shortfall increase, that is they possess an inverse relationship. This was evident for the majority during COVID and pre-COVID. that this is true for the TTSE All T&T Index as well as the selected cryptocurrencies examined. During the COVID period, the market risk of cryptocurrencies specifically at the 1% level were significantly larger when compared to the pre-COVID period. It was anticipated that the pandemic would have impacted the market risk of Caribbean equity.

GARCH Results and Interpretation

Table 20. ARCH Effects Results

ARCH Effects	Pre-COVID	COVID
BSE	0.9600	0.8037
JSE	0.0019	0.0000
TTSE	0.4292	0.0001
BTC	0.0613	0.9324
ETH	0.6443	0.9477
USDT	0.0000	0.0000
BNB	0.0104	0.0000
ADA	0.1569	0.0000

This section delved into the coefficient values obtained from the variations of ARCH modelling performed and primarily focused on the stock exchanges and crypto currencies that exhibited ARCH effects and Bitcoin shown in Table 19. The confidence level of 5% was used to determine whether ARCH effects were present. Prior to COVID, only one stock exchange (JSE) and two cryptocurrencies (USDT and BNB) revealed the presence of ARCH effects. During COVID, only BSE, BTC and ETH did not experience ARCH effects. The ARCH, GARCH and TGARCH models were applied where applicable. Table 20 and Table 21 shows the coefficients for the respective models prior to and during COVID.

Table 21. Coefficients for ARCH, GARCH and TGARCH models for the pre-COVID period

Pre-COVID	ARCH	GARCH		TGARCH		
	Alpha α	Alpha α	Beta β	Alpha α	Beta β	Gamma γ
BSE	N/A	N/A	N/A	N/A	N/A	N/A
JSE	0.219785	0.072334	0.902132	0.107487	0.904274	-0.091319
TTSE	N/A	N/A	N/A	N/A	N/A	N/A
BTC	N/A	N/A	N/A	N/A	N/A	N/A
ETH	N/A	N/A	N/A	N/A	N/A	N/A
USDT	0.429050	0.284865	0.475013	0.096223	0.537681	0.350070
BNB	0.176708	0.194453	0.247517	0.058267	0.837773	0.056434
ADA	N/A	N/A	N/A	N/A	N/A	N/A

Table 22. Coefficients for ARCH, GARCH and TGARCH models for the COVID period

COVID	ARCH	GARCH		TGARCH		
	Alpha α	Alpha α	Beta β	Alpha α	Beta β	Gamma γ
BSE	N/A	N/A	N/A	N/A	N/A	N/A
JSE	0.412176	0.133737	0.745723	0.160626	0.756186	-0.062691
TTSE	0.192702	0.166290	0.787637	0.188792	0.786027	-0.042913
BTC	N/A	N/A	N/A	N/A	N/A	N/A
ETH	N/A	N/A	N/A	N/A	N/A	N/A
USDT	8.183943	0.215815	0.823218	0.297281	0.825879	-0.192343
BNB	0.386918	0.202980	0.764187	0.192643	0.763519	0.021167
ADA	0.237042	0.333885	0.577835	0.307010	0.572929	0.059567

In this analysis, the alpha coefficients for the stock returns and cryptocurrencies are assessed using an ARCH (1) model. During the pandemic, the alpha value of USDT exceeded one, implying that the variance of the error term is explosive and will recurrently increase over periods. For JSE, BNB and ADA there was an increase in the alpha values between the two time periods. This indicated that returns of the previous period are more likely to have a significant impact on the returns of the present period during the pandemic than before the pandemic. Next, the GARCH (1,1) is employed. Apart from USDT during the pandemic, the stationarity condition was met elsewise for both datasets. For USDT, this implies that the model would be explosive in nature and unstable. The remaining cryptocurrencies and stocks exchanges have high stationarity suggesting that there is a slow decay of the effect as mean reversion occurs. Lastly, the TGARCH model was utilised to accommodate and appropriately consider negative and positive news that might have occurred. Good news impacts the conditional variance through alpha and bad news by means of the summation of alpha and gamma. Overall, gamma values are not able to supersede the alpha values indicating that the impact of the bad news does not dominate the good news. The stationarity condition is not satisfied by JSE (pre-COVID) and USDT (during COVID). Like the results of the GARCH model, the remaining cryptocurrencies and stocks exchanges have high stationarity suggesting that there is a slow decay of the effect as mean reversion occurs.

Conclusion

This paper sought to investigate the market risk of the selected Caribbean markets and cryptocurrencies prior to and during the pandemic by utilizing the Value at Risk (VaR) methodology. The market risk was investigated using three methods: historical, parametric, and modified. In terms of market risk, the results have shown that during the pandemic there has been increased levels of market risk for both the Caribbean equity markets and selected cryptocurrencies. However, the magnitude of increase was larger within the cryptocurrency markets. Additionally, the study examined the spillover effects of cryptocurrencies on Caribbean equity markets through the Vector Autoregressive Model (VAR). The VAR indicated that there is the presence of spillover effects from cryptocurrency markets Caribbean equity markets. However, these spillover effects are insignificant.

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