Are the Crypto Markets Shock Resilient to COVID-19? A Comparative Investigation of Trading Prices and Volumes

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ABSTRACT

The aim of this study is to explore and investigate empirically the impact of Covid-19 pandemic on price and volume dynamics in crypto markets. The study makes use of two data samples, but these samples are analyzed separately and independently. The first sample consists of top five crypto currencies in terms of market capitalization (Bitcoin, Ethereum, XRP, Binance coin and Litecoin) as of 7 November 2020. The second one is made up of the bottom five crypto currencies among the top 40 crypto currencies (FTX Token, Huobi Token, Filecoin, Dash and Decreed) as of 7 November 2020 again. The data among the top five crypto currencies ranges from 2014 to 2021 and the data among the bottom five crypto currencies ranges from 2018 to 2021. The empirical analysis confirms presence of compelling evidence for intra-and-inter long run relationship between price and volume dynamics within the crypto market irrespective of whether it is pre-pandemic or pandemic period. More so, there is convincing evidence from the results that much of the variance among the prices and volumes of the top five crypto currencies is attributed to the Bitcoin price-volume dynamics.

Key words: *Crypto currencies, Cointegration, VECM, Covid-19, resilience*

JEL Codes: G11, G12, G15

1. INTRODUCTION

To meet its imminent daily needs and wants, humanity has been subjected to trading with one another. Trading has been a tradition that dates back to the time of creation of humankind as it was and continues to be a survival strategy. Down the centuries trade has taken various forms and shapes and it continues to evolve as time progresses. The history of trade has evolved from bartering to the use of commodity money to the adoption of fiat (paper) money and now into digital currencies over the past 10,000 years (J.M. Yuki, 2018). The evolution of currencies continues up to date and has given birth to one of the most phenomenal developments of the 21st century which is the establishment of virtual currencies. These are digital currencies in electronic form that can be stored and transacted via dedicated software or electronic platforms e.g., mobile phones, computer applications or designated electronic wallets. The transaction involving digital currencies is internet based via secured dedicated networks and as well as in privacy.

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The popularity of virtual currencies has accelerated the acceptance and recognition of virtual currencies as a safe and credible form of currency, enjoys the same functions as that of traditional currencies. A crypto currency is a form of virtual and digital currency that can be accepted as a means of exchange or as a store of value. Magro, (2016) described crypto currencies as a peer-to-peer encrypted network that facilitates virtual barter. Throughout the years crypto currencies have evolved in their functionality from just been a peer-to-peer payment system into investment instruments, store of asset value as well as hedging options for both prospective and adept investors. The growth of crypto currency markets has been exponential and unprecedented. Currently, there are over 5000 crypto currencies serving different purposes (protocols).

However, the crypto currency market has not been free from misery and controversies. The volatility clustering within crypto currency market is unparalleled to any other commodity market. The market capitalization of most of the top crypto currencies has been soaring and this means simultaneously price and traded volumes of such currencies have been ascending incessantly. This has been the nature of most of such crypto currencies since the time they gained much traction.

Nevertheless, on the 11th of March 2020 World Health Organization (WHO) proclaimed Covid-19 outbreak as a global pandemic and like many other commodity markets, crypto currencies' market has its own reaction to the external economic shock induced by Covid-19 pandemic. This has resulted in the change in behavior of price and volume relationship in many commodity markets including within crypto currency market.

Since the emergence of the Covid-19 pandemic, the academic arena is witnessing a plethora of studies analyzing the impact of the pandemic on different commodity markets. One of such markets than has received much attention is the crypto currency market. Coerbet at al (2022) examined the interlinkages between crypto currency price volatility and liquidity during the pandemic period. The results of this novel study indicated the potential of crypto currencies an investment safe haven especially during periods of unprecedented economic shock. In another study Emna et al (2020) explored the performance of crypto currency market during the pandemic using a multifractal approach and the results of this study implied that Covid-19 pandemic had a positive impact on the performance of crypto currency market.

Additionally, Yousaf and Ali (2021) investigated the return and volatility spillovers between S&P 500 and crypto currencies during the pre-Covid-19 and Covid-19 period using a VAR-BEKK-AGARCH model. The results of the study could not establish the return and volatility spillovers between the S&P 500 and the crypto currencies during the pre-Covid-19 era. However, during the pandemic period and unidirectional volatility spillover between the two was established. Studies by Meichen et al (2022) focused on untangling the price discrepancies in the crypto currency market during the pandemic period. The study's results implied that the price discrepancies were more in Bitcoin prices and also in countries with many confirmed Covid-19 cases.

However, despite convincing literature on the subject there still exist lack of empirical studies analyzing, unravelling, and untangling on how the price and volume dynamics of crypto currencies evolved during the COVID-19 pandemic. This is a research gap that need much focus and attention as the price-volume relationship in any commodity market is particularly important in understanding the dynamics of that market. The main objective of this study is in testing the resilience of the prices-volume relationships in the crypto currency when subjected to an unprecedented economic shock caused by the Covid-19 pandemic. This study is unique in that it tests this resilience using independent data samples from the top crypto currencies which control almost 80% of the crypto market and also bottom 5 crypto currencies in the top 40 cryptos in order to capture the dynamic behaviors of the crypto currencies within different categories and influences in the cryptocurrency market.

The empirical results of this study show that all crypto currencies under this study are integrated at order 1 i.e. I (1). The empirical analysis substantially confirms the presence of strong evidence for intra-and-inter long run relationship between price and volume dynamics within the crypto market irrespective of whether it is pre-pandemic or pandemic period. More so, there is convincing evidence from the results that much of the variance among the prices and volumes of the top five cryptocurrencies is attributed to the Bitcoin price-volume dynamics. This implies that it is critical for crypto market traders, investors and portfolio managers, before making any investment decision must consider the dynamics of price and trading volumes of Bitcoin as it hugely impacts the prices and volumes of other altcoins.

The study is divided into different chapters and each chapter focuses on a certain aspect of the study. The first chapter is the introductory chapter that gives the background of the study. This is followed by the Literature Review which consist of the preliminary work done before about this research question. The third chapter explain the statistical methods used during this study. The fourth chapter shows the results and the analysis of the results obtained from the study. The last chapter is the conclusion which summarizes and give brief information about all the stages that the study has undertaken as well as giving necessary policy recommendations needed.

2. LITERATURE REVIEW

Since their inception, cryptocurrency markets have managed to gain traction among both researchers and investors. The last decade has witnessed and continues to witness an unprecedented boom in crypto currency landscape. This has made crypto currency market behaviors to be one of the topical issues on both economic and political fronts. As a result, this popularity has exacerbated much research in this field and more robust research are currently underway. Crypto currency markets unlike traditional markets are very dynamic in nature. Available literature attests to the significant research done before however, more research is needed as the field remains underexplored.

Price-volume dynamics represent the reactions and adjustments of market players in an event of an economic shock (positive or negative). In 1970s, two theoretical models for stock markets' price volume relationship were proposed. These two are the Sequential Information Arrival (SIA) Model (Copeland, 1976) and the Mixture of Distributions Hypothesis (MDH) (Epps, 1978).

The SIA hypothesis firstly propounded by Copeland (1976) and was later developed by Jennings et al. (1981) and then improved by Starks and Saatcioglu (1995) assumes that new information is received sequentially by both buyers and sellers in stock market. This sequency of receiving information determines the equilibrium of stock price and trading volume in market. This hypothesis postulates that in the cryptocurrency market information dissemination sequentially occurs to investors. This means the equilibrium price is only achieved when all investors are informed about the new information.

The Mixture of Distribution Hypothesis (MDH) was developed as a result of works of different research such as Clark (1973), Epps and Epps (1976), Harris and Gurel (1986) and Andersen (1996). This hypothesis indicates the existence of a positive correlation between asset prices and trading volume (Yamak et al. 2019). The MDH hypothesis posits that the crypto currency trading volumes and price volatilities respond to changes in the speed in which latest information reaches the crypto market. This means the speed or rate at which new information arrives to the crypto market helps in explaining the GARCH effects in crypto currency returns (Epps and Epps, 1976).

The popularity of crypto currencies has also drawn academic attention. Preliminary academic intervention on this subject mainly focused on expounding the whole concept, that is the mechanisms and protocols behind crypto currencies. Studies by Peters et al. (2015), ElBahrawy et al. (2017), Gandal et al. (2018), Farell (2015) and Böhme et al. (2015) are some of the early studies that focused on giving an overview on the subject of crypto currencies especially Bitcoin, elucidating its mechanisms and components. Subsequently, empirical studies regarding crypto-currency market have also been conducted over the years. Yi et al. (2018) explored the dynamic and static volatility changes among crypto currencies. Katsiampa (2019) examined the volatility dynamics of five major crypto currencies namely Bitcoin, Litecoin, Ripple, Ether and Stella. Bouri et al. (2020) examined the time-varying measurement of volatility connectedness involving 15 crypto currencies. On similar way, Conrad et al. (2018) extracted the long-and-short term volatility components of crypto currencies using the GARCH-MIDAS model.

Supplementary empirical studies on the crypto-currency market focused on the relation between crypto currencies and other assets such as gold prices, oil prices and other stock indices. For example, Okorie and Lin (2020) examined the volatility connectedness between crude oil and crypto-currency prices. Junior et al. (2020) using returns series of gold and 8 crypto-currencies explored and compared both their symmetric and asymmetric dependency structure. Kurka (2019), Chemkha et al. (2020), Andrada-Félix et al. (2020) and Baumöhl (2019) conducted different studies investigating the volatility connectedness between crypto currencies and major fiat currencies such as Euro, Japanese Yen and US Dollar. Gallant et al. (1992) studied the joint dynamics of price and trading volumes and concluded that more can be learned which cannot be achieved by analyzing them in a univariate form.

Karpoff (1987) gave the following as four main important factors of studying the price-volume relationship: (i), It gives intuition of the financial market structure, (ii), it is ideal for studies that involving price and volume data from which to draw inferences, (iii), the relation is critical to the debacle over the empirical distribution of speculative stock prices and (iv), price-volume relationship dynamics have remarkable implication for research into future markets.
Despite the flourishing literature concerning the crypto market, the price-volume in this market dynamics has been under-explored and remain scarcely examined. Like any commodity market, crypto currency market also reacts to economic shocks. Covid-19 ignited economic shock that has some effects on the global economy and this study seeks to empirically explore and analyze the price-volume dynamics within the crypto currency market before and during the period of Covid-

19 pandemic. The general objective lies in testing the resilience of this crypto currency price-volume relationship when confronted with a shock.

3. DATA AND METHODOLOGY

The study uses two categories of crypto currencies to have a more robust approach (that test different categories) and results to the investigations of the price-volume dynamics in the crypto currency market prior and during the Covid-19 pandemic. The first category is made up to five top crypto currencies in respect of their market capitalization as of 7 November 2020. These currencies are Bitcoin, Ethereum, XRP, Binance coin and Litecoin. The second category consist of the bottom five crypto currencies among the top 40 cryptocurrencies in accordance with their market capitalization as at 7 November 2020. These currencies are FTX Token, Huobi Token, Filecoin, Dash and Decreed.

The prices and volumes of cryptocurrencies are extracted from https://coinmarketcap.com/. The data of the top five crypto currencies range from 10 April 2014 to 7 November 2021 and the data of the bottom five crypto currencies range from 15 September 2018 to 7 November 2021. To avoid the problems of scale and for easing the analysis the natural logarithmic transformation of the data is taken. Table 3.1 lists the 20-time series of crypto currencies under consideration in this study.

Top Five Currencies	Abbreviation	Bottom Five Currencies	Abbreviation
Bitcoin Price	lnbp	FTX Token Price	lnftxp
Bitcoin Volume	lnbv	FTX Token Volume	lnftxv
Ethereum Price	lnep	Huobi Token Price	lnhtp
Ethereum Volume	lnev	Huobi Token Volume	lnhtv
XRP Price	lnxp	Filecoin Price	lnfcp
XRP Volume	lnxv	Filecoin Volume	lnfcv
Binance Coin Price	lnbnp	Dash Price	lndp
Binance Coin Volume	lnbnv	Dash Volume	lndv
Litecoin Price	lnlp	Decred Price	lndrp
Litecoin Volume	lnlv	Decred Volume	lndrv

Table 3.1 Crypto currencies under the study

3.1. Unit Root Tests

As, dealing with time series, the unit root/stationarity testing is the preliminary step to avoid the possibility of spurious regression, therefore unit root/stationarity testing has been conducted. Unit root/stationarity testing is used to determine whether a time series is stationary or non-stationary in nature. The non-stationarity of a time series implies that its mean and variance changes over time. This pre-testing for unit root/stationarity is especially important in preventing spurious regression that results from the use of non-stationary time series (Harris and Sollis 2003). A stationary time series comprises of constant mean, constant variance, and constant auto-covariance. This pre-testing for unit root/stationarity also provides the order of integration of each time series, which then helps in the selection of an appropriate model.

We used three-unit root tests in order to come up with results that are more robust and to see whether they do or do not confirm each other's results. More so, this was done to make sure that our results are valid and not biased towards a specific technique. These approaches are Augmented Dickey-Fuller (1979), Kwiatkowski et al. (1992) and Elliott et al. (1996). The null hypothesis of Augmented Dickey-Fuller (1979) and Elliott et al. (1996) state that the time series has properties of a unit root whereas the alternative hypothesis states that the time series is stationary. The third test the Kwiatkowski et al. (1992) has a null hypothesis that states that time series is stationary whereas its alternative hypothesis is that time series is not stationary.

The unit root tests are used to determine if time series are stationary or not. If time series are found to be non-stationary at their level and if they are stationary at first difference then it means they are integrated of order one I(1).

3.2. Johansen Test of Cointegration:

Granger (1980) cited that if the time series are I(1), then it is possible that there exists a stable long run relationship i.e. cointegration among them. The Johansen (1995) cointegration test is used to test the cointegration i.e. existence of a stable long run relationship among a number of time series. Unlike two-step Engle-Granger (1980), Johansen (1995) cointegration has the capacity for testing of more than one cointegrating vectors (Sjo, 2008). Johansen (1995) test also treats all the time series in the model as endogenous, unlike other techniques available in existing literature, which only treats one time series as endogenous and considers the rest as exogenous. This means Johansen cointegration approach allows two or more cointegrating relationships to co-exist. However, before conducting the Johansen (1995) cointegration test an appropriate or optimal lag length has to be determined. Too small or over parameterized lag length can lead to model misspecification (Wooldridge, 2009).

Johansen (1995) cointegration considers a Vector Auto-Regressive (VAR) model of order k:

$$y_t = \beta_1\, y_{t-1} + \beta_2\, y_{t-2} + \ldots \ldots + \beta_k y_{t-k} + \mu_t \tag{3.1}$$

Where y_t is a g-vector of I(1) time series, $\beta_k{'}s$ are the coefficient matrices of each lag and μ_t is the white noise disturbance term. By adding the error correcting components, the above equation can be transformed into a Vector Error Correction Model (VECM) as follows:

$$\Delta y_t = \Pi y_{t-1} + \Gamma_1\, \Delta y_{t-1} + \Gamma_2\, \Delta y_{t-1} + \Gamma_{k-1}\, \Delta y_{t-(k-1)} + \mu_t \tag{3.2}$$

Where $\Delta y_t = y_t - y_{t-1}$, k is the number of lags and the two matrices $\Pi = \left(\sum_{i=1}^{k} B_i\right) - \mathrm{I}_g$ and $\Gamma i = \left(\sum_{j=1}^{i} B_J\right) - \mathrm{I}_g$. Where Π represents the long run coefficient matrices, Γi constitute of short-term dynamics and "g" denotes the number of time series in the model.

Johansen and Juselius (1990) proposed the trace test statistic and the maximum eigenvalue statistic for making the inference about the number of cointegrating vectors. However, we are using the trace test as it is more powerful than maximum eigenvalue test as cited by Lutkepohl et al. (2000). The trace test statistic is formulated as:

$$\lambda_{trace}(r) = -T \sum_{i=r+1}^{n} \ln(1 - \hat{\lambda}_r) \qquad (3.3)$$

Where T is the sample size, r is the number of cointegrating vectors and $\hat{\lambda}$ is eigenvalues. The sequentially tested set of Johansen null and alternative hypotheses are as follows:

$$H_0: r = 0 \; versus \; H_1: 0 < r \leq g \qquad (3.4)$$
$$H_0: r = 1 \; versus \; H_1: 1 < r \leq g \qquad (3.5)$$
$$H_0: r = 2 \; versus \; H_1: 2 < r \leq g \qquad (3.6)$$
$$H_0: r = g - 1 \; versus \; H_1: r = g \qquad (3.7)$$

Where r denotes the number of cointegrating vectors under the relevant null hypothesis. However, if the first null hypothesis is rejected such as $H_0 : r = 0$ and the second $H_0 : r = 1$ cannot be rejected then we can conclude that there is one cointegrating vector and the same goes for more than one cointegrating vectors.

We make use of two types of models. The first model looks how the price and volume dynamics were before Covid-19 pandemic is whereas the second model tries to assess the price and trade volume dynamics during the Covid-19 pandemic. To examine the price and volume inter and intra dynamics among crypto currencies considered in this study, the Vector Error Correction Models (VECMs) are:

$$Y_t = \begin{bmatrix} lnbp_t \\ lnbv_t \\ lnep_t \\ lnev_t \\ lnxp_t \\ lnxv_t \\ lnbnp_t \\ lnbnv_t \\ lnlp_t \\ lnlv_t \end{bmatrix} \qquad Et_t = \begin{bmatrix} E_{1t} \\ E_{2t} \\ E_{3t} \\ E_{4t} \\ E_{5t} \\ E_{6t} \\ E_{7t} \\ E_{8t} \\ E_{9t} \\ E_{10t} \end{bmatrix}$$

$$\Delta Y_t = \Pi\beta Y_{t-1} + \Gamma i \Delta Y_{t-1} + E_t \qquad (3.8)$$
$$\Delta Y_t = \Pi\beta Y_{t-1} + \Gamma i \Delta Y_{t-1} + \theta COVID_t + E_t \qquad (3.9)$$

The first equation 3.8 checks for the price-volume relationships between the top 5 crypto currencies in the period before the Covid-19 pandemic whereas equation 3.9 considers the price-volume relations before and during the pandemic. Where ΔY_t denotes the changes in all the top 5 crypto currencies' prices and volumes in the model, $\Pi\beta Y_{t-1}$ is the Error Correctional Term and $\Gamma i \Delta Y_{t-1}$ constitutes of the short-run relations in the model. $COVID_t = 1$ on and after 11-03-2020 and $COVID_t = 0$ elsewhere.

$$Y_t = \begin{bmatrix} lnftxp_t \\ lnftxv_t \\ lnhtp_t \\ lnhtv_t \\ lnfcp_t \\ lnfcv_t \\ lndp_t \\ lndv_t \\ lndrp_t \\ lndrv_t \end{bmatrix} \qquad Et_t = \begin{bmatrix} E_{1t} \\ E_{2t} \\ E_{3t} \\ E_{4t} \\ E_{5t} \\ E_{6t} \\ E_{7t} \\ E_{8t} \\ E_{9t} \\ E_{10t} \end{bmatrix}$$

$$\Delta Y_t = \Pi\beta Y_{t-1} + \Gamma i \Delta Y_{t-1} + E_t \tag{3.10}$$

$$\Delta Y_t = \Pi\beta Y_{t-1} + \Gamma i \Delta Y_{t-1} + \theta COVID_t + E_t \tag{3.11}$$

Equation 3.10 checks for the price-volume relationships between the bottom 5 crypto currencies in the period before the Covid-19 pandemic whereas equation 3.11 considers the price-volume relations before and during the pandemic. Where ΔY_t denotes the changes in all the bottom 5 crypto currencies' prices and volumes in the model, $\Pi\beta Y_{t-1}$ is the Error Correctional Term and $\Gamma i \Delta Y_{t-1}$ constitutes of the short-run relations in the model. $COVID_t = 1$ on and after 11-03-2020 and $COVID_t = 0$ elsewhere.

3.3. Variance Decomposition

Variance decomposition analysis is an important tool regarding the causal relationship of variables beyond the in-sample period. It forecast errors and determines relationships among the variables. These models give the proportion of the variation of a variable due to the shock to itself and the shock to other variables. According to Bessler, (1985), variance decomposition can be termed as causality tests outside the estimation time period. The variance decompositions are obtained from the Moving Average (MA) model derived from an unrestricted VAR model.

4. EMPIRICAL RESULTS

The descriptive statistics for top five and bottom five crypto currencies are presented in Table 4.1 and Table 4.2 respectively. According to the descriptive statistics in Table 4.1, Bitcoin price and volume have the highest mean among all of the cryptos. Moreover, Bitcoin price has the highest maximum price whereas XRP price has the lowest minimum price. Among the volumes, Bitcoin volume has the highest maximum volume and Binance Coin has the lowest minimum volume. Bitcoin price has also the highest standard deviation compared to others. This translates that Bitcoin price is the most volatile currency compared to other currencies.

	BP	EP	XP	BNCP	LTCP	BV	EV	XV	LTCV	BNCV
Mean	9315	357.8	0.40	16.54	81.43	1.85E+10	7.94E+09	1.87E+09	2.31E+09	2.04E+08
Median	8244.6	256.01	0.30	15.28	60.64	1.47E+10	6.07E+09	1.12E+09	1.98E+09	1.72E+08
Maximum	40797.6	1718.6	3.38	67.84	358.34	1.23E+11	6.07E+10	3.50E+10	1.80E+10	1.43E+09
Minimum	3154.9	84.31	0.14	0.45	23.46	7.68E+08	2.54E+08	20566500	51786200	9284.000
Std. Dev.	5770.3	270.70	0.33	9.88	51.94	1.63E+10	8.11E+09	3.10E+09	2.29E+09	1.86E+08

Skewness	2.85	1.92	4.29	0.71	2.01	1.562	2.26	5.087	1.933	1.415
Kurtosis	12.99	6.83	28.37	3.69	7.61	6.52	10.32	36.75	9.062	6.35
Jarque-Bera	6997.7	1558	37989	132	1980	1172	3926	65744	2736	1017
Observations	1270	1270	1270	1270	1270	1270	1270	1270	1270	1270

Table 4.1 Descriptive Statistics of top five crypto currencies

According to the descriptive statistic Table 4.2, Dash price has the highest mean among the prices. Additionally, Dash price has the highest maximum price, and its volume has the highest maximum volume. FTX Token price has the lowest price and Filecoin volume has the lowest volume. Dash price and volume are the most volatile among the rest since they have the highest values of the standard deviation.

	FTXP	**HTP**	**FCP**	**DP**	**DRP**	**FTXV**	**HTV**	**FCV**	**DV**	**DRV**
Mean	3.268	4.041	12.866	80.277	20.202	8102832	1.64E+08	58472996	6.35E+08	33759100
Median	2.89	4.07	6.27	74.54	16.88	4308038.	1.26E+08	10890409	4.23E+08	15912047
Maximum	14.84	8.11	59.26	148.38	79.72	1.01E+08	1.30E+09	7.13E+08	1.41E+10	1.47E+08
Minimum	1.15	2.4	2.43	39.87	9.3	510850	51315132	51124	1.37E+08	1918527
Std. Dev.	2.11	0.78	9.92	19.94	11.64	11152537	1.20E+08	98184152	1.24E+09	38388421
Skewness	2.56	0.80	0.82	0.55	2.72	3.89	3.75	2.35	9.41	1.37
Kurtosis	10.56	6.007	2.90	3.18	10.47	22.55	26.62	9.39	98.15	3.34
Jarque-Bera	1804	252	58	28	1849	9574	13281	1360	203437.4	164
Observations	519	519	519	519	519	519	519	519	519	519

Table 4.2 Descriptive Statistics of bottom five crypto currencies

4.1. Unit Root Test Results

The Augmented Dicky Fuller (ADF) Unit root test results from Table 4.3, show that all the top five crypto currencies with the minor exception of Litecoin volume have unit roots at level. At levels Litecoin volume is stationary at 5% or higher level of significance only when trend is considered in the testing equation. However, at first difference all crypto currencies are stationary at a 1% level of significance. This translates that all series under consideration in this category are concluded as integrated of order 1, i.e. I(1).

The ERS Optimal Point test results in Table 4.3 indicate that the null hypothesis of having a unit root for all the time series in top 5 cannot be rejected except for XRP prices, Binance Coin volume and Litecoin volume. This means that except these three, at the levels all series have a unit root. At levels XRP prices, Binance coin volume and Litecoin volume are all stationary at 5% level of significance. Nevertheless, at first difference all series in this category are stationary at 1% level of significance. This means that all series in this category appear to be integrated of order one I(1).

Having a null hypothesis of stationary, the results of Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test shows that the null hypothesis is rejected at 1% significance level in all series. However, at first difference, the null hypothesis cannot be rejected for all series except for Bitcoin price, Ethereum coin price and Binance coin price. These results again indicate that the prices and volumes of top five crypto currencies are concluded as integrated of order 1 i.e. I(1).

Test	Price & Volume Time Series	Top Five Crypto currencies						Conclusion
		At Level			First Difference			
		None	Constant	Trend	None	Constant	Trend	
Augmented Dicky Fuller (ADF) Test	BP	2.05	0.604	-2.074	-51.8***	-51.877***	-51.923***	I(1)
	BV	1.552	-0.43	-3.018	-13.94***	-14.040***	-14.046***	I(1)
	EP	0.949	-1.612	-1.876	-7.59***	-7.795***	-7.810***	I(1)
	EV	1.568	-1.655	-2.478	-11.39***	-11.547***	-11.567***	I(1)
	XP	-1.04	-0.929	-2.358	-14.92***	-14.933***	-14.941***	I(1)
	XV	1.525	-0.938	-2.619	-12.56***	-12.682***	-12.679***	I(1)
	BNCP	0.840	-2.093	-2.702	-10.60***	-10.674***	-10.651***	I(1)
	BNCV	0.416	-1.707	-3.242*	-24.37***	-25.373***	-25.363***	I(1)
	LTCP	0.343	-0.459	-2.371	-51.49***	-51.489***	-51.522***	I(1)
	LTCV	0.331	-1.216	-4.16***	-23.88***	-23.897***	-23.903***	I(1)
ERS Point Optimal	BP		66.27	42.558		0.023***	0.071***	I(1)
	BV		12.001	13.855		0.645***	1.497***	I(1)
	EP		187.73	55.42		0.070***	0.115***	I(1)
	EV		55.074	8.784		0.12***	0.568***	I(1)
	XP		16.43	25.525		0.014***	0.053***	I(1)
	XV		9.945	4.474**		0.265***	0.976***	I(1)
	BCP		90.557	36.102		4.059*	4.354**	I(1)
	BCV		6.728	1.028**		0.998***	1.647***	I(1)
	LTCP		15.788	49.755		0.034***	0.075***	I(1)
	LTCV		7.528	4.697**		0.16***	0.537***	I(1)
Kwiatkowski-Phillips-Schmidt-Shin (KPSS) Test	BP		5.531***	0.511***		0.340	0.146*	I(1)
	BV		6.086***	0.507***		0.044	0.033	I(1)
	EP		3.685***	1.060***		0.316	0.176**	I(1)
	EV		5.097***	0.874***		0.063	0.02	I(1)
	XP		4.717***	0.596***		0.127	0.113	I(1)
	XV		5.890***	0.49***		0.019	0.018	I(1)
	BCP		2.360***	0.314***		0.235	0.124**	I(1)
	BCV		2.882***	0.15***		0.051	0.041	I(1)
	LTCP		4.236***	0.542***		0.338	0.197	I(1)
	LTCV		5.645***	0.566***		0.159	0.086	I(1)

Table 4.3 Unit Root Test analysis for top 5 crypto currencies
*Note: ***, ** and * show the null hypothesis' rejection at 1%, 5% and 10% significance level respectively*

The Augmented Dickey-Fuller test results of the bottom five crypto currencies depicted in Table 4.4, show that at level, the null hypothesis cannot be rejected for all series under observation apart from Huobi Token volume and Filecoin volume. Therefore, it can be concluded that at the level the remaining series has a unit root. At level Huobi Token volume is stationary at 10% level of significance and Filecoin volume is stationary at 5% level of significance. However, at first difference all series in this category are stationary at a 1% level of significance. This means that all series under consideration in this category are concluded as integrated of order 1, i.e., I(1).

The results of the ERS Optimal Point test indicate that the null of unit root for all the time series in this category cannot be rejected except for three (FTX volume, Filecoin volume and Decree volume). At level FTX volume, Filecoin volume and Decree volume are all stationary at 5% level of significance. At first difference, the results indicate that all series in this category are stationary at 1% level of significance. This means that all series in this category appear to be integrated to order one, I(1).

Having null hypothesis of stationary the results of KPSS show that the null hypothesis is rejected at 1% significant level in all series under this test. At first difference, the null hypothesis cannot be rejected for all series except for Huobi Token volume and Dash price. This means that again all series in this category are concluded as integrated of order 1 i.e. I(1).

		Bottom Five Crypto currencies						
Test	Price & Volume Time Series	At Level			First Difference			Conclusion
		None	Constant	Trend	None	Constant	Trend	
Augmented Dickey Fuller (ADF Test)	FTXP	0.281	-1.076	-1.720	-11.023***	-11.018***	-11.237***	I(1)
	FTXV	0.379	-2.568	-2.983	-17.363***	-17.354***	-17.343***	I(1)
	HTP	0.61	-1.114	-2.633	-10.25***	-10.277***	-10.366***	I(1)
	HTV	0.397	-3.4	-3.408*	-12.325***	-12.327***	-12.315***	I(1)
	FCP	-0.397	-1.206	-1.848	-9.969***	-9.964***	-10.204***	I(1)
	FCV	0.99	-0.896	-3.919**	-10.35***	-10.409***	-10.429***	I(1)
	DP	0.471	-1.158	-0.940	-20.084***	-20.119***	-20.134***	I(1)
	DV	0.963	-1.195	-2.802	-18.419***	18.463***	-18.462***	I(1)
	DRP	0.605	-1.332	-1.355	-17.921***	-17.978***	-17.976***	I(1)
	DRV	0.698	-1.311	-2.725	-15.173***	-15.202***	-15.196***	I(1)
ERS Optimal Point	FTXP		13.567	39.105		0.16***	0.343***	I(1)
	FTXV		1.735	4.357*		0.176***	0.652***	I(1)
	HTP		5.677	10.476		0.105***	0.001***	I(1)
	HTV		0.614	1.100		0.41***	1.331***	I(1)
	FCP		7.185	25.04		0.169***	0.417***	I(1)
	FCV		6.897	0.364**		0.309***	0.978***	I(1)
	DP		59.358	35.758		0.026***	0.094***	I(1)
	DV		17.148	8.38		0.278***	0.689***	I(1)
	DRP		65.583	41.14		0.134***	0.191***	I(1)
	DRV		4.601	5.28**		0.596***	1.142***	I(1)
Kwiatkowski-Phillips-Schmidt-Shin (KPSS) Test	FTXP		0.676**	0.495***		0.456*	0.032	I(1)
	FTXV		0.423*	0.314***		0.083	0.053	I(1)
	HTP		1.587***	0.092*		0.187	0.059	I(1)
	HTV		0.252**	0.271***		0.134	0.128*	I(1)
	FCP		1.149***	0.893***		0.249	0.041	I(1)
	FCV		3.587***	0.221***		0.065	0.033	I(1)

	DP		3.804***	1.144***		0.237	0.152*	I(1)
	DV		5.495***	0.959***		0.117	0.120	I(1)
	DRP		2.083***	0.956***		0.224	0.173	I(1)
	DRV		4.179***	0.477**		0.038	0.04	I(1)

Table 4.4 Unit Root Test analysis for bottom five crypto currencies
*Note: ***, ** and * show the null hypothesis' rejection at 1%, 5% and 10% significance level respectively*

4.2. Johansen Cointegration Test Results

The unit root tests' results have shown that all the time series under consideration in this study are integrated of order one I(1). Therefore, Johansen (1995) Cointegration is conducted to determine the existence of long run relationship among the series (crypto currencies) and how many they are within the scope of this study. However, before conducting any cointegration technique an appropriate or optimal lag length has to be determined. Too small or over parameterized lag length can lead to model misspecification as cited by Wooldridge, (2009). The Johansen Cointegration test was conducted using the 3rd specification (intercept, no trend in CE and test VAR) of the Johansen Cointegration (1995) test which is more theoretically plausible. However, the results of this 3rd specification of the Johansen Cointegration Test are not much different from other specifications.

Table A-1 and A-2 in Appendix A show that the optimal lag length for unrestricted VAR model and AIC and SC are the information criteria used but the study adopts a more parsimonious approach. The Schwarz Information Criteria (SIC) is considered as it is much preferred than AIC (Aysan et al, 2021). The SIC selects lag 1 as optimal.

Table 4.4 and 4.5 show the results of the Johansen cointegration test for both top five crypto currencies and bottom five crypto currencies, respectively. The number of cointegrating vectors under the hypothesis is denoted by r . The results of the top five crypto currencies (both without Covid-19 as exogenous and with Covid-19 as exogenous variable) show that it has 6 cointegrating vectors at 1% significance level. However, to get more information and a better perspective of the cointegration among these series 5 cointegrating equations are used in this study. As for the bottom five crypto currencies show that its series (both without Covid-19 as exogenous and with Covid-19 as exogenous variable) have 4 cointegration vectors at 5% level of significance.

		Without COVID as Exogenous		With COVID as Exogenous	
Null Hypothesis	Alternative Hypothesis	Trace Test Stat	Prob	Trace Test Stat	Prob
$r = 0$	$r > 0$	785.2387***	0.0000	808.7395***	0.0001
$r \leq 1$	$r > 1$	540.8758***	0.0001	563.1673***	0.0001
$r \leq 2$	$r > 2$	349.2551***	0.0000	368.4653***	0.0000
$r \leq 3$	$r > 3$	195.4133***	0.0000	207.9041***	0.0000
$r \leq 4$	$r > 4$	126.2052***	0.0001	138.5610***	0.0000
$r \leq 5$	$r > 5$	79.23365***	0.0073	85.01597***	0.0019
$r \leq 6$	$r > 6$	47.66430*	0.0521	46.72144*	0.0636
$r \leq 7$	$r > 7$	20.51234	0.3888	15.70361	0.7329

Table 4.4 Unrestricted Cointegration top five crypto currencies (Trace Test Statistic)

		Without COVID as Exogenous		**With COVID as Exogenous**	
Null Hypothesis	Alternative Hypothesis	Trace Test Stat	Prob	Trace Test Stat	Prob
$r = 0$	$r > 0$	382.2863***	0.0000	401.2038***	0.0000
$r \leq 1$	$r > 1$	275.3480***	0.0000	286.8777***	0.0000
$r \leq 2$	$r > 2$	194.2767***	0.0002	205.6086***	0.0000
$r \leq 3$	$r > 3$	135.2316**	0.0113	144.1825***	0.0022
$r \leq 4$	$r > 4$	79.80568	0.3711	88.63302	0.1397
$r \leq 5$	$r > 5$	48.22261	0.7128	53.07110	0.5021
$r \leq 6$	$r > 6$	30.10739	0.7135	33.70601	0.5180

Table 4.5 Unrestricted Cointegration bottom five crypto currencies (Trace Test Statistic)

The long-run relationship between the top five crypto currencies under this study are signified and shown through the Cointegrating Vectors (CVs). The long run coefficients of the top five crypto currencies are tabulated in Table 4.6 after imposition of the Johansen normalization restrictions. According to the results in Table 4.6, the volumes of Bitcoin, Ethereum and Litecoin are statistically crucial in the determination of the closing price of Bitcoin before Covid-19 pandemic is regarded. However, during Covid-19 pandemic the volumes of Bitcoin, Ethereum, XRP and Litecoin are all statistically decisive in determining the closing price of Bitcoin

Regarding the closing price of Ethereum before the Covid-19 pandemic, the trading volumes of Bitcoin, Ethereum, Binance coin and Litecoin are statistically crucial. With the inclusion of the Covid-19 pandemic the trading volumes of Bitcoin, Ethereum, XRP and Litecoin are statistically critical for determining the closing price of Ethereum. With regards to the closing price of XRP, the volumes of four crypto currencies (Ethereum, XRP, Binance coin and Litecoin) are statistically crucial before the Covid-19 pandemic. However, during the Covid-19, the trading volumes of five crypto currencies (Bitcoin, Ethereum, XRP, Binance coin and Litecoin are statistically crucial.

Before Covid-19 pandemic, volumes of three crypto currencies (Bitcoin, XRP and Binance coin) are significantly impacting the closing price of Binance coin. However, when the pandemic is given due consideration (during covid 19), the trading volumes of Bitcoin, Ethereum, XRP, Binance coin and Litecoin all have statistically relevant impact on the Binance coin closing price. Before taking Covid-19 pandemic into account, volume of Bitcoin, Ethereum, Binance coin and Litecoin have a crucial effect on Litecoin's closing price. When the Covid-19 pandemic is finally regarded the volume of the same four crypto currencies (Bitcoin, Ethereum, Binance coin and Litecoin) maintained their significance in explaining the closing price of Litecoin. The results of the intra and inter relationship between the prices and volumes of the top five crypto currencies have shown some form of resilience against the shock induced by Covid-19 pandemic

	Top Five Crypto currencies									
	Without COVID					**With COVID**				
	CV1	**CV2**	**CV3**	**CV4**	**CV5**	**CV1**	**CV2**	**CV3**	**CV4**	**CV5**
BP	1					1				
EP		1					1			
XP			1					1		
BNP				1					1	
LTP					1					1
BV	**-4.4***** (0.498)	**-7.6***** (0.999)	0.118 (0.234)	**1.7***** (0.335)	**-4.3***** (0.57)	**-7.6***** (1.028)	**-12***** (1.73)	**-0.7***** (0.24)	**0.6***** (0.24)	**-7.56***** (1.03)
EV	**3.3***** (0.467)	**5.9***** (0.935)	**1.7***** (0.221)	**-0.412** (0.313)	**4.9***** (0.53)	**2.01**** (0.96)	**4.4***** (1.62)	**1.7***** (0.22)	**-0.9***** (0.23)	**4.06***** (0.96)
XV	-0.17 (0.193)	0.23 (0.388)	**-1.0***** (0.09)	**-0.9***** (0.13)	-0.13 (0.22)	**0.82**** (0.39)	**1.5***** (0.66)	**-0.9***** (0.089)	**-0.5***** (0.09)	0.72 (0.39)
BNV	-0.361 (0.184)	**-1.4***** (0.369)	**-0.9***** (0.09)	**-0.7***** (0.123)	**-1.4***** (0.21)	**-0.075** (0.37)	**-0.99** (0.63)	**-0.8***** (0.09)	**-0.6***** (0.08)	**-1.09**** (0.37)
LTC	**0.98***** (0.25)	**2.5***** (0.5)	**0.3***** (0.12)	0.23 (0.17)	**0.8***** (0.28)	**3.4***** (0,54)	**5.6***** (0.921)	**0.7***** (0.12)	**0.6***** (0.12)	**2.9***** (0.55)

Table 4.6 Normalized Cointegration Coefficients

The study further explores the short-run impact of the Covid-19 pandemic on both closing prices and trading volumes of all the top five crypto currencies under the study. The results in 4.7, indicate that Covid-19 pandemic has a statistically significant positive short-run impact on trading volumes of all crypto currencies considered for the study (Bitcoin, Ethereum, XRP, Binance coin and Litecoin).

The negative economic shock induced by Covid-19 pandemic on traditional investment instruments (stocks, bonds, and cash) has been overwhelming, subsequently crypto currencies have posed as an alternative form of saving money or investments. As crypto currencies have shown a characteristic of resilience against any form of external economic shock (Covid-19 pandemic), both experienced and aspirant investors have turned to cryptocurrencies as an alternative to the traditional investment assets. This has exacerbated the acceptance of many crypto currencies as either a form of currency or an investment option. Consequently, because of these dynamics the transaction volumes of any crypto currencies have been increasing at unparalleled mode. However, as for the impact of Covid-19 pandemic on the closing prices of the top five crypto currencies no statistically significant impact could be established.

Top Five Crypto currencies									
BP	EP	XP	BNP	LTP	BV	EV	XV	BNV	LTC
0.0019	0.0032	0.0077	-0.005	-0.0051	**0.09*****	**0.05*****	**0.145*****	**0.100*****	**0.067*****
(0.004)	(0.005)	(0.006)	(0.006)	(0.006)	(0.019)	(0.021)	(0.034)	(0.038)	(0.024)

Table 4.7 Short-run impact of Covid-19

The long run coefficients of the bottom five crypto currencies are tabulated in Table 4.7 According to the results in the table the volumes of Filecoin, Dash and Decreed have a significant effect on the closing price of FTX Token when Covid-19 pandemic is excluded. However, when the pandemic is considered, the volumes of four crypto currencies (FTX Token, Filecoin, Dash and Decreed) are statistically crucial in the closing price of FTX Token. As for the closing price of Huobi Token when the pandemic is not regarded, the trading volumes of FTX Token, Huobi Token, Dash and Decreed are statistically crucial. When Covid-19 pandemic is taken into consideration the Huobi Token, Filecoin, Dash and Decreed trading volumes are statistically crucial explaining the closing price of Huobi Token.

When not considering Covid-19 pandemic volumes of three crypto currencies (FTX Token, Filecoin and Dash are significantly affecting the price of Filecoin. However, after the pandemic is recognized, all the trading volumes of FTX Token, Huobi Token, Filecoin, Dash and Decreed have statistically critical impact effect on the prices of Filecoin. Before taking Covid-19 pandemic into account, volume of Filecoin, Dash and Decreed have a crucial effect on the closing price of Dash. Nevertheless, when Covid-19 pandemic is finally considered the volume of the same three crypto currencies (Filecoin, Dash and Decreed) maintained their significance in explaining the closing price of Filecoin.

Bottom Five Crypto currencies								
	Without COVID				**With COVID**			
	CV1	**CV2**	**CV3**	**CV4**	**CV1**	**CV2**	**CV3**	**CV4**
FTXP	1				1			
HTP		1				1		
FCP			1				1	
DP				1				1
DRP								
FTXV	-0.106 (1.04)	**21.1***** (5.27)	**45.93***** (6.22)	12.44 (7.85)	-0.57 (1.10)	6.88 (5.53)	**38.15***** (5.72)	7.38 (8.58)
HTV	-0.003 (0.03)	**-1.2***** (0.19)	0.31 (0.22)	0.14 (0.282)	0.008 (0.03)	**-0.83***** (0.19)	**0.46***** (0.20)	0.23 (0.30)
FCV	**0.04***** (0.01)	0.09 (0.04)	**-0.55***** (0.063)	**0.29***** (0.08)	**0.05***** (0.013)	**0.28***** (0.07)	**-0.426***** (0.068)	**0.38***** (0.102)
DV	**-0.18***** (0.03)	**-0.54***** (0.15)	**-1.07***** (0.18)	**-1.63***** (0.22)	**-0.19***** (0.03)	**-0.56***** (0.16)	**-1.082***** (0.16)	**-1.67***** (0.25)
DRV	**0.08***** (0.02)	**0.3***** (0.08)	0.21 (0.095)	**0.39***** (0.12)	**0.08***** (0.02)	**0.37***** (0.09)	**0.26***** (0.085)	**0.44***** (0.13)

Table 4.7 Normalized Cointegration Coefficients

The study also investigated the short-run impact of Covid-19 pandemic on the closing prices and trading volumes of all the bottom five crypto currencies under this study. According to the results shown in Table 4.8, Covid-19 pandemic did not have a statistically critical impact on all the trading volumes of all these crypto currencies except on Huobi Token volume.

Since, Huobi Token is a native currency of Huobi Crypto Exchange, its trading volumes are mostly reliant on the reputation of the Huobi Crypto Exchange. In July 2020 (same period as Covid-19), the Chinese police arrested a criminal gang that was involved in selling fake Huobi Token. Few months later the Chief Operating Officer (COO) of Huobi Crypto Exchange Zhu Jiawei was arrested on charges of money laundering by the Chinese authorities. All these developments one after the other affected the reputation of both Huobi Crypto Exchange and Huobi Token. In the same period the Huobi Crypto Exchange market lost its customers (especially the risk averse ones) and later few transactions were recorded. This had a direct impact on the volumes of Huobi Token.

As for the other bottom five crypto currency the short run impact on these currencies is statistically insignificant. This is largely due to their lower market share in the crypto currency market. The markets share of these crypto currencies is inconsequential when compared to other influential crypto currencies such as Bitcoin and Ethereum. However, when a shock befalls a market, the influential crypto currencies are likely to be affected than those that are less influential. This is because the lower the trading volume and price a crypto currency commands, the lesser it is likely to be affected by random shocks in the market. So, the pandemic has no direct impact on these currencies.

Bottom Five Crypto currencies									
FTXP	HTP	FCP	DP	DRP	FTXV	HTV	FCV	DV	DRV
0.00042	0.0022	0.0056	0.003	0.0063	0.00139	**-0.13*****	-0.089	-0.048	0.0008
(0.0015)	(0.0049)	(0.014)	(0.007)	(0.007)	(0.001)	(0.038)	(0.098)	(0.036)	(0.058)

Table 4.8 Short-run impact of Covid-19

4.3. Variance Decomposition

We decompose each crypto-currency's variance attributed to a shock in itself or other crypto currencies in order to investigate the interrelationships among Top five crypto currencies during Covid-19 pandemic. It is evident from Figure 4.1 that the variation of closing prices Bitcoin due to itself is exceedingly high almost 100%. More so, the amount of variation attributed to closing prices of Bitcoin in closing prices of other crypto currencies (Ethereum, XRP, Binance coin and Litecoin) is remarkably high averaging at almost 45%.

As for to the variation of closing prices of Ethereum on itself is high approximately at 40% and also the attribution of its variance in closing prices of XRP, Binance coin and Litecoin is also fairly significant averaging at around 10%. However, the results show that the variation of closing prices of XRP, Binance coin and Litecoin due to themselves respectively is high but their influence is extremely low on other crypto currencies. The results indicate that closing prices of Bitcoin followed by Ethereum have a significant amount of influence in the variation of closing prices of itself and other crypto currencies.

One other side, the variation in trading volume of Bitcoin in itself is around 80%. Accordingly, Bitcoin trading volume has a significant amount of the variation on trade volume of Ethereum, XRP, Binance coin and Litecoin. The trading volume of Ethereum has also a significant impact on the variation in itself and also in other crypto currencies such as XRP, Binance coin and Litecoin. The trading volumes of the remaining crypto currencies (XRP, Binance coin and Litecoin) have significant portions of variation in themselves respectively but their influence in the variation of other crypto currencies is not incredibly significant. However, the results suggest that trading volume of Bitcoin followed by Ethereum have a more significant amount of influence than the trading volumes of other crypto currencies (XRP, Binance coin and Litecoin) in the variation of trading volume of itself and other crypto-currencies.

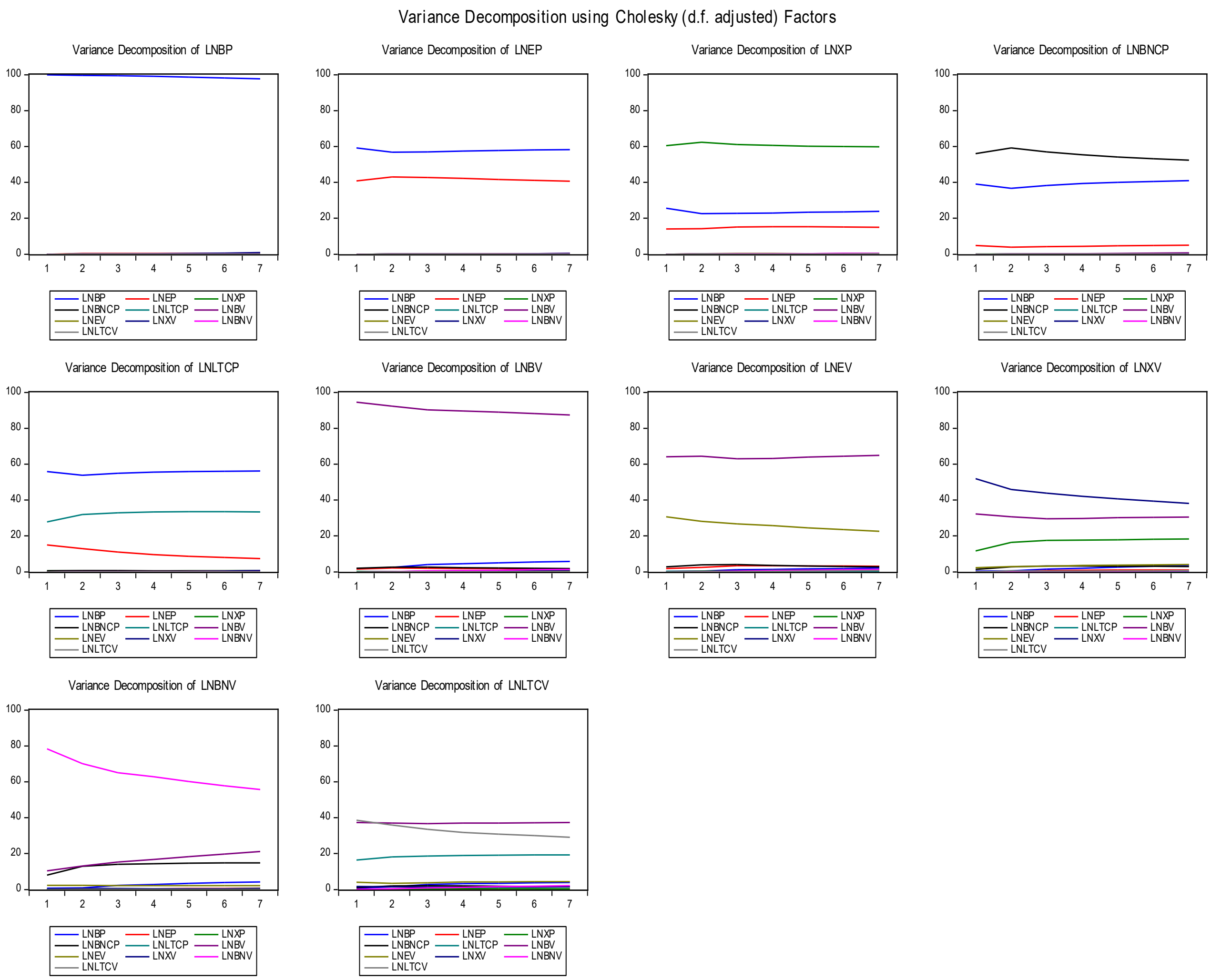

Figure 4.1 Variance Decomposition Analysis of top five crypto currencies

The study further explores each crypto currency's variance attributed to a shock in itself as well as to other crypto currencies among the bottom five crypto currencies that are under this study during the Covid-19 pandemic. According to the results the variation of the closing price of FTX Token due to a shock in itself is very high at approximately 95%. Additionally, the proportion of variance credited to the closing price of FTX Token in closing prices of other crypto currencies such as Huobi Token, Filecoin, Dash and Decred has been averaging 50%, 5%, 45% and 40% respectively.

The results also indicate that the variance of the closing price of Huobi Token due to a shock on itself is approximately at 50%. However, its variance on the closing prices of other currencies such as FTX, Filecoin, Dash and Decreed is incredibly low. Filecoin's closing price variance on itself is extremely high at 95% but also like Huobi Token, its variance on the closing prices of other currencies is very low and inconsequential.

Furthermore, the results show that the variation of the closing prices of Dash and Decreed due to themselves respectively is high (around 50% and 60% respectively) but their influence is very low on other crypto currencies. The results indicate that the closing price of FTX Toke has the most significant (when compared to others) amount of influence in the variation of closing prices of itself and other cryptocurrencies.

As for the variance of the trading volume of FTX Token on itself is around 80%. However, FTX Token trading volume has a significant amount of the variance on the trade volume of Huobi Token (30%), Filecoin (10%), Dash (10%) and Decreed (5%). The trading volume of Huobi Token has also a significant impact on the variation in itself at approximately 60% but very low on other crypto currencies.

The results conclude that the trading volumes of the other bottom five crypto currencies (Filecoin, Dash and Decreed) have sizable portion of variation on themselves respectively but their influence on the variation of other crypto currencies is not much significant. However, the results suggest that trading volume of FTX Token has a more significant amount of influence than the trading volumes of other crypto currencies (XRP, Binance coin and Litecoin) in the variation of trading volume of itself and other crypto currencies. This makes it the most influential among them.

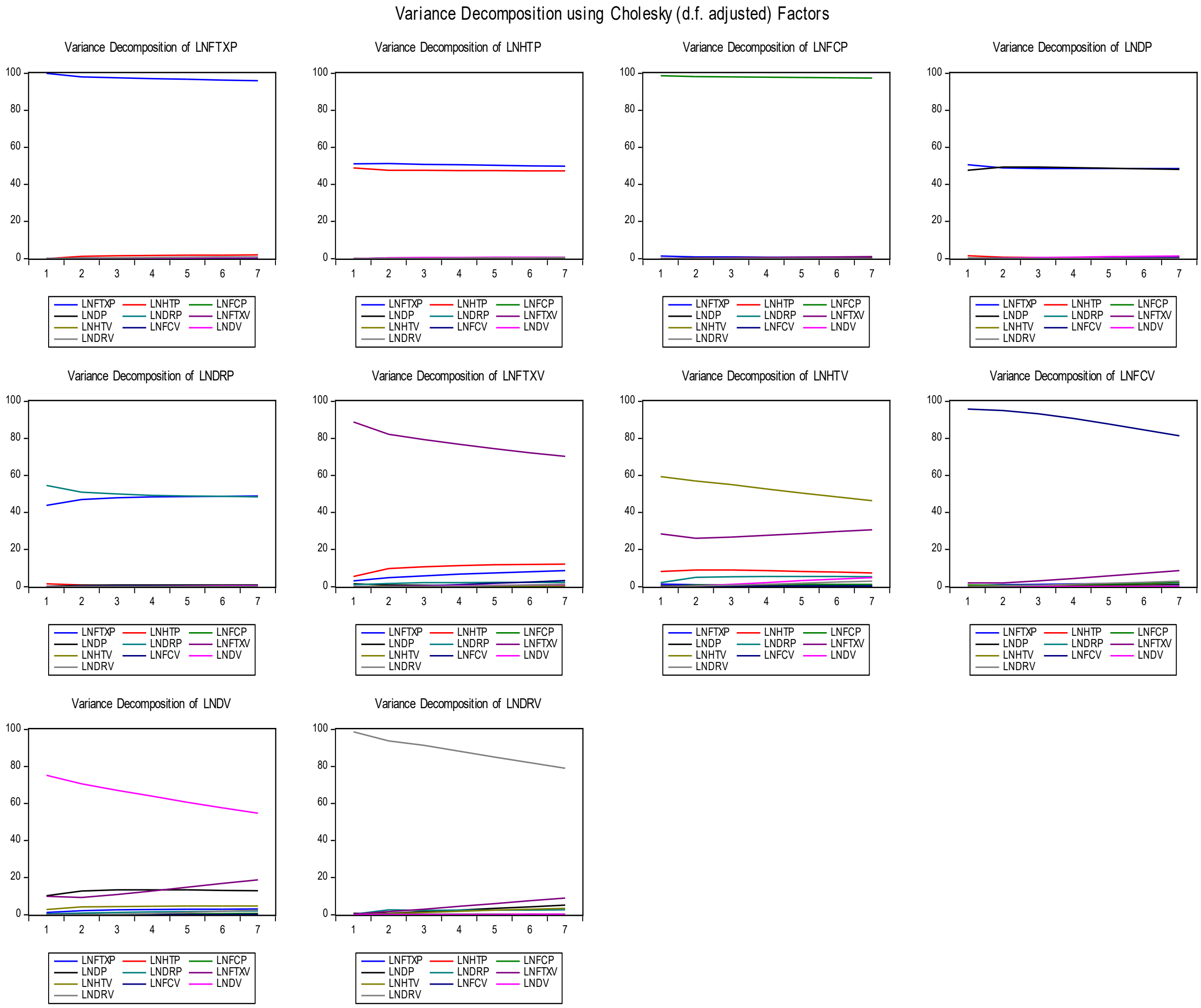

Figure 4.2 Variance Decomposition Analysis of bottom five crypto currencies

The results of these two variance decompositions show that among the top five crypto currencies Bitcoin price and trading volume is more responsible for price-volume variation among other cryptocurrencies compared to others. However, among the bottom five crypto currencies no dominant crypto currencies could be determined in explaining the price-volume variations in other crypto currencies. This implies the influence and the dominance of Bitcoin in the crypto currency market.

5. CONCLUSION AND POLICY IMPLICATIONS

The apprehension of the relationship between price and volume is an important step toward understanding the dynamics of any market whether it's a commodity market or stock market. Gallant et al. (1992) cites that by studying the joint dynamics of price and trading volumes more can be learned which cannot be achieved by analyzing them in their univariate form.

This study make use of two data samples, but these samples are analyzed separately and independently. The first sample consist of top five crypto currencies in terms of market capitalization (Bitcoin, Ethereum, XRP, Binance coin and Litecoin) as of 7 November 2020. The second one is made up of the bottom five crypto currencies among the top 40 crypto currencies (FTX Token, Huobi Token, Filecoin, Dash and Decreed) as of 7 November 2020 again. The data of the top-5 crypto currencies range from 10 April 2014 to 7 November 2021 and the data of the bottom five crypto currencies range from 15 September 2018 to 7 November 2021.

The empirical results reveal that all crypto currencies under this study regardless of their category are integrated at order 1 i.e. I (1). There is further evidence from the study of intra-and-inter long run relationships among the prices and volumes of both the Top five and the Bottom five crypto currencies irrespective of whether its pre-pandemic period or during the pandemic period. The results also show that Covid-19 pandemic had a strong impact on the price-volume dynamics within the crypto currency market. The covid-19 shock was capable of altering and changing the nature and direction of these long-run price-volume relations.

The study also explored the short-run impact of the pandemic on both categories of crypto currencies under the study. Positive short-run impact was established among all the trading volumes of the top five crypto currencies. Consequently, among the bottom five currencies the impact of the pandemic was very minimum only significant on Huobi Token trading volume. This show that the shock induced by the pandemic had an immediate and direct impact on more influential crypto currencies (top five crypto currencies) compared to those that are not influential (bottom five crypto currencies).

Furthermore, the study decomposed the variance decomposition of the two categories of these crypto currencies during the Covid-19 pandemic. The results of these two variance decompositions show that among the top five crypto currencies Bitcoin's price and trading volume are more responsible for price-volume variations among other crypto currencies compared to others. However, among the bottom five crypto currencies no dominant crypto currencies could be determined in explaining the price-volume variations in other crypto currencies. This implies the influence and the dominance of Bitcoin in the crypto currency market.

These conclusions recommend that crypto market traders, investors, and portfolio managers, before making any investment decisions must consider the dynamics of the price and trading volumes of Bitcoin as they hugely impact the prices and volumes of other crypto currency. Moreover, the findings help future crypto investors in forecasting the price and volume dynamics of crypto currency especially confronted with an external shock capable of causing a financial crisis. It also helps investors in designing effective and efficient trading strategies in crypto market such as portfolio diversification.

APPENDIX

	Top Five Crypto currencies							
	Without COVID as Exogenous				With COVID as Exogenous			
Lag Length	0	1	2	3	0	1	2	3
Schwarz SIC	9.443	**-18.908***	-18.71	-18.49	7.975	**-18.884***	-18.68	-18.448
Akaike AIC	9.402	-19.36	-19.57	**-19.75***	7.893	-19.373	-19.58	**-19.75***

Appendix 1: Lag Length Criteria for Top Five Crypto currencies

	Bottom Five Crypto currencies							
	Without COVID as Exogenous				With COVID as Exogenous			
Lag Length	0	1	2	3	0	1	2	3
Schwarz SC	-1.006	**-20.355***	-19.678	-18.770	-2.388	**-20.290***	-19.6	-18.68
Akaike AIC	-1.090	-21.271	**-21.427***	-21.352	-2.555	-21.289	**-21.43***	-21.34

Appendix 2: Lag Length Criteria for Top Five Crypto currencies

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