Cryptocurrency Returns and Volatility Spillover During an Era of Uncertainty: COVID-19 and VIX

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Abstract: This study investigates the volatility of cryptocurrencies during the uncertainty created by COVID-19 and the Chicago Board Options Exchange Volatility Index (VIX). Hence, the relationship between cryptocurrencies in the pre- and post-COVID-19 era was introduced into a mean equation that applied the VAR (1)—BEKK GARCH-M (1,1) method to the eight largest market volume cryptocurrencies. Descriptive statistics show the Dogecoin has the most volatility, BNB has the highest return, and BTC has the lowest volatility. Due to the lag in its return during the pre-COVID-19 time frame, BTC harms other coins' returns. Other coins' returns, including their own, are increased by the Dogecoin's one-period lagged return. Notably, only BNB, XLM, and XRP were statistically significantly impacted by VIX spikes. This study highlights the fact that cryptocurrencies experience first-instance (average) volatility. Bitcoin's long-term uncertainties statistically significantly and favorably enhance other cryptocurrencies' long-term uncertainties.
Keywords: Cryptocurrency, Uncertainty, COVID-19, Volatility, BEKK GARCH-M (1,1) method
JEL: F01, F40, F62

Introduction

In volatile economies, traditional investment instruments may lose their appeal, prompting investors to seek alternatives. At this point, cryptocurrencies can be an alternative instrument. However, global uncertainties may affect cryptocurrencies. Serious price fluctuations can occur, especially in unstable economic environments (Gherghina et al., 2024). Recent increases in global uncertainty have been a constant wake-up call for cryptocurrency markets (Kumar et al., 2023). The popularity of and interest in cryptocurrencies has increased in recent years from investors, speculators, academics, and the media (Mensi et al., 2021). There are two main gaps in the literature on the impact of COVID-19 and global uncertainties on cryptocurrencies (Kumar et al., 2022). First, conclusive evidence is lacking on return and volatility spillovers between leading cryptocurrencies, which is crucial for any investment decision regarding portfolio diversification and hedging strategies. Second, evidence is lacking on return and volatility spillovers between leading cryptocurrencies during catastrophic events, such as the COVID-19 pandemic. With a focus on sustainable cryptocurrencies during the COVID-19 period, it is crucial to examine the impact of uncertainty or volatility on the cryptocurrency market (Haq et al., 2023). This study will fill this gap in the literature by assessing the impact of COVID-19 and global uncertainties on cryptocurrencies.

Studies addressing cryptocurrencies' uncertainty and risks include an analysis of Bitcoin's volatility, approach to hedging strategies based on cryptocurrencies, and spillover effects (Rojas Rincón, 2024). There are several dimensions according to which our study diverges from previous studies. First, this work used daily data from 2018 (503 observations) and 2022 (571 observations). Compared to Al-Shboul et al. (2022), Apergis (2022), and Corbet et al. (2022), this study's sample was longer. Second, compared to Aysan et al. (2019), Cui and Maghyereh (2022), Demir et al. (2020), Al-Shboul et al. (2022), Wang et al. (2019), and Raza et al. (2022), eight cryptocurrencies were explored, including Bitcoin, Ethereum, ADA, BNB, XRP, XLM, LITE, and Dogecoin. Third, the recent literature has employed various methodologies to examine interconnectedness and volatility transmission in cryptocurrency markets. The Diebold and Yilmaz (2012) spillover approach has gained prominence due to its ability to provide a clear, interpretable measure of interdependence among asset returns and volatilities (Fasanya et al., 2020; Lamine et al., 2023). Alternatively, many researchers have utilized the GARCH family of models to investigate volatility dynamics in cryptocurrency markets. Particularly the DCC-GARCH model has been widely applied to examine spillover effects and dynamic correlations among cryptocurrencies and other assets (Afjal and Sajeev, 2022; Aydoğan et al., 2022; Gupta and Chaudhary, 2022). The EGARCH model has also captured asymmetric volatility impacts, providing insights into the potential for the differential effects of positive and negative shocks on market volatility (Gupta and Chaudhary, 2022; Idrees and Akhtar, 2023). By leveraging these methodological approaches, this study contributes to the growing literature on cryptocurrency market dynamics and their interactions using the BEKK–GARCH model. Understanding these relationships is crucial for investors optimizing portfolio diversification strategies and for policymakers developing appropriate regulatory frameworks for this rapidly evolving market. This study also employs the methodological approaches of Kroner and Sultan (1993) and Kroner and Ng (1998) to examine hedge ratios and optimal portfolio weights for policymakers and investors.

Literature Review

The impact of macroeconomic factors (Al-Khazali et al., 2018; Gurrib et al., 2019; Deniz and Teker, 2019; Corbet et al., 2019) and the use of Bitcoin as an alternative portfolio diversification tool (Qarni and Gulzar, 2021; Vo et al., 2022) are some of the topics covered in studies on the prices and returns of cryptocurrencies. In highly globalized financial markets, understanding the interaction dynamics of financial indicators has recently become very important for decision makers due to the increasing interdependence and contagion between countries. In particular, financial shocks have a large impact on the financial variables and markets of the entire world's economy by increasing their volatility (Aydemir et al., 2021). Although Bitcoin first comes to mind regarding cryptocurrencies, there are 23,845 cryptocurrencies today (https://coinmarketcap.com/). The role of cryptocurrencies as diversifiers, hedges, or safe havens has been categorized by previous studies (Hsu et al., 2021). In the literature, studies have been conducted not only on Bitcoin but also on the relationship between different cryptocurrencies or cryptocurrencies with each other. In this regard, Koutmos (2018) measured the interdependence between 18 major cryptocurrencies and found that (i) Bitcoin is the dominant contributor to return and volatility spillovers across all sampled cryptocurrencies; (ii) return and volatility spillovers have steadily increased over time; and (iii) there are spikes in spillovers during major news events related to cryptocurrencies. Among the studies examining return interconnectedness and volatility spillovers in cryptocurrencies, Ji et al. (2019) showed that return shocks originating from Litecoin and Bitcoin have the greatest impact on other cryptocurrencies. Similarly, Kyriazis (2019) found that Bitcoin is the most influential among cryptocurrencies, mainly as a recipient of spillovers, while Ethereum, Litecoin, and Ripple are the cryptocurrencies linked to Bitcoin. In their research examining the interconnectedness of 12 cryptocurrencies, Bouri et al. (2020b) found significant co-bounce activity, especially in Ripple, Bitcoin, and Litecoin. Yi et al. (2018) investigated the volatility linkages between cryptocurrencies. They found that cryptocurrencies with high market capitalization transmit larger volatility spillovers to other cryptocurrencies, and Bitcoin contributes significant volatility spillovers to other cryptocurrencies but does not dominate the entire market. Although the literature terms Bitcoin the most influential instrument among cryptocurrencies and mentions its relationship with various crypto assets, a structural change has emerged in the interconnectedness of cryptocurrencies after COVID-19 (Kumar et al., 2022). Bitcoin lost its dominant "hedger" position during this period, while Litecoin became the most dominant "hedger" and/or "safe" asset before and during the pandemic period (Al-Shboul et al., 2022). Exploring the interconnectedness of cryptocurrency returns and changes in the uncertainty of cryptocurrency policy (UCRY), Raza et al. (2022) showed that the UCRY policy index distinguishes itself from other cryptocurrencies by having very low interconnectedness between XRP, NEM, Menero, and ETH. They found that any change in the returns of Bitcoin, DOGE, and Litecoin, together with a change in the UCRY policy index, spreads risk to other cryptocurrencies. Foglia and Dai (2021) estimated the cryptocurrency uncertainty (UCYR) index using economic policy uncertainty (EPU) and found that EPU affects the UCRYP index. That is, EPUs have positive predictive power for cryptocurrency uncertainty, suggesting a pass-through between the two indices. Wang et al. (2019) studied the risk spillovers from EPUs to Bitcoins using MVQ-MC-ViaR and Granger causality and found that the spillovers from EPUs to Bitcoins are marginal and that Bitcoins are a safe haven/diversifier during EPU shocks. For sustainable cryptocurrencies, it is important to examine the volatility spillover effect of EPU and volatility measures (Haq et al., 2023).

The rise in public interest in Bitcoin, a fascinating phenomenon in financial markets, has sparked several controversies. Interestingly, Kristoufek (2013) and Garcia et al. (2014) found a correlation between Bitcoin prices and searches on Google, Wikipedia, social media platforms, etc. To identify the key elements influencing Bitcoin pricing in particular, Bitcoin appears to be a speculative asset (Kristoufek, 2015). Nonetheless, Bitcoin also exhibits the traits of a typical financial asset, distinguishing it from other assets in this regard. In addition to these distinctive traits, studies have also highlighted its function as a safe harbor to escape global uncertainty. The VIX of 14 developed and emerging stock markets showed that Bitcoin functions as a hedge against global uncertainty (Bouri et al., 2017). Additionally, a number of studies (Aysan et al., 2019; Demir et al., 2018) conclude that economic policy uncertainties and geopolitical risks can predict Bitcoin returns and that Bitcoin can act as a hedge against uncertainty. This is because Bitcoin serves as a safe haven or diversifier in times of economic unpredictability (Wang et al., 2019).

In addition to global uncertainties, one of the most important uncertainty factors that has emerged recently is COVID-19. The vast majority of studies have examined return and volatility spillovers among cryptocurrencies considering the impact of the COVID-19 pandemic as it rages across the globe (Cui and Maghyereh, 2022). Several studies have examined the dynamic relationship between cryptocurrencies and other financial assets during the COVID-19 turmoil. They also explored the safe haven properties of cryptocurrencies for market practitioners (Hsu et al., 2021). The search for useful risk management and hedging strategies and investor demand for safe-haven assets was reinvigorated by the outbreak of the COVID-19 pandemic in early 2020 (Aharon et al., 2021). In the literature, researchers have studied the fact that cryptocurrencies can be an exit point in the uncertain environment brought on by COVID-19, negatively affecting returns or having no effect (Demir et al., 2020; Kristoufek, 2020; Naeem et al., 2021). Demir et al. (2020) examined the relationship between Bitcoin, Ethereum, and Ripple and COVID-19 cases/deaths and found that cryptocurrencies play a hedging role against the uncertainty caused by COVID-19. In contrast, Naeem et al. (2021) examined the efficiency of cryptocurrencies using one-hour data from Bitcoin, Ethereum, Litecoin, and Ripple and showed that the COVID-19 pandemic negatively affected the efficiency of four cryptocurrencies. Furthermore, unprecedented catastrophic events, such as the COVID-19 pandemic, have been found to have negative effects on the efficiency of leading cryptocurrencies. Kristoufek (2020) also examined the correlations between Bitcoin and two benchmarks (S&P 500 and VIX) and compared them to gold, a traditional safe-haven asset. Consequently, he concluded that Bitcoin's status as a safe haven is unfounded and that gold is the clear winner in this comparison. Similarly, Mokni et al. (2021) illustrated that Bitcoin does not act as a strong hedge against aggregate economic policy uncertainty (EPU). Shahzad et al. (2019) argue that Bitcoin, gold, and the commodity index can each be considered weak safe-haven assets in some circumstances and that their safe-haven roles vary over time. Bouri et al. (2020a) investigated the safe-haven characteristics of Bitcoin, gold, and the commodity index and found that Bitcoin is the most promising safe-haven asset. Theiri (2024) noted that geopolitical risks, such as the COVID-19 pandemic, have led to increased volatility and contagion effects in cryptocurrency markets, with this effect being particularly pronounced during severe geopolitical instability. This study also demonstrated that cryptocurrencies are interconnected and influenced by broader market sentiments and global events. According to Mensi et al. (2024), cryptocurrency's connectivity increased during COVID-19 and returned to pre-pandemic levels after stock markets recovered. Moreover, cryptocurrency markets reacted asymmetrically to uncertainty, exhibiting potential hedge and safe-haven characteristics. Yousaf et al. (2024) investigated the static and dynamic interdependence of Islamic cryptocurrency and metal markets. They found that Islamic cryptocurrencies are the recipients of both return and volatility spillovers, while most metals act as transmitters of these spillovers. They also found that dynamic spillovers intensified during the COVID-19 period compared to the pre-COVID-19 period. They found that return stickiness was a short-term phenomenon, while volatility stickiness was a long-term phenomenon. Phiri and Anyikwa (2024) examined the return and volatility spreads of cryptocurrencies at the onset and aftermath of the COVID-19 pandemic and found that the return correlation was stronger than the volatility correlation.

The coronavirus crisis that gripped the world in 2020 and 2021 and has continued in various forms and degrees ever since initially threatened to tear the world apart and profoundly impacted us for years to come. It had a large and varied impact on most regions and nations throughout 2020 and the early, middle, and later months of 2021; however, its impact has been very uneven across the board. The principle of uneven development implies that the power structures of the global political economy, especially in the countries at the center, through their production networks, commodity chains, political structures, and financial dynamics, give them advantages that put them in a good position to deal with crises, even if they were not initially prepared for them (O'Hara, 2021). Shahzad et al. (2022a) investigated the hedging role of assets such as Bitcoin, gold, and US VIX futures against downward movements in BRICS stock market indices after COVID-19. They found that Bitcoin played a weak hedging role, while gold in China and VIX futures in Brazil, Russia, India, and South Africa displayed a strong hedging role. Another study in G7 countries found that gold is a safer haven than Bitcoin (Shahzad et al., 2020). Overall, cryptocurrencies showed heterogeneous responses during the COVID-19 process and played an important role in the dynamic interconnectedness of all market conditions (Al-Shboul et al., 2022). Haq (2022) investigated the link between the cryptocurrency index of environmental attention (ICEA) and four main green financial assets between 2014 and 2021: the Dow Jones World Sustainability Index (DJWSI), the Dow Jones Sustainability Index Australia (DJSAI), S&P Global Green Bonds (GB), and the S&P Global Clean Energy Index (GCEI). Haq (2022) found higher volatility during the COVID-19 period despite the heterogeneity of connectivity in the relevant years. Similarly, a number of studies have found heterogeneity in the behavior of investors in cryptocurrency markets and increased volatility during COVID-19 (Yousaf et al., 2021; Shahzad et al., 2021). According to Fang et al. (2019), Bitcoin's volatility is affected by economic uncertainty, and investors and practitioners in the Bitcoin market should closely monitor the level of global economic policy uncertainty when making investment decisions. In their study of how geopolitical risk affects cryptocurrency pricing, Long et al. (2022) discovered that cryptocurrencies with low geopolitical betas outperformed those with high geopolitical betas. Crypto valuations plummeted from $3 trillion in November 2021 to $977 billion in June 2022 with the outbreak of the Russia–Ukraine conflict. This could be attributed to a change in investment behavior. Investors massively sold off due to heightened inflation fears caused by the Russia–Ukraine conflict and herding behavior in cryptocurrency markets (Khalfaoui et al., 2023). Kumar et al. (2023), who measured the spillover effect of the Russia–Ukraine conflict on cryptocurrencies as a geopolitical factor, observed a high level of spillovers in the pre-conflict period, which was maintained during the military confrontation. However, they observed that several digital assets changed their status from net receiver to net transmitter and vice versa, and the topology of network connectedness changed during the Russia–Ukraine conflict. Poddar et al. (2023) found that the yield connectedness and volatility spillover networks of cryptocurrencies were scattered before and concentrated during the COVID-19 period and highly concentrated during the Russian–Ukrainian War. The EPU index has influenced cryptocurrency volatility spillovers but not their return connectedness. Azimli (2024) found that cryptocurrencies are affected by major events, such as COVID-19, with one exception, the Russia–Ukraine War, which did not increase the total connectivity between cryptocurrencies. Investigating the interaction between economic uncertainty and cryptocurrency behavior, Będowska-Sójka et al. (2024) found that cryptocurrency returns are dynamically and positively correlated with stock market and oil volatility, but not with other uncertainty indicators. They also discovered that, in terms of volatility spillovers, the shift from uncertainty indices to cryptocurrency markets is weak but intensified during turbulent periods, such as the COVID-19 pandemic or the Ukraine war.

Methodology

The Econometric Model

In this study, the relationship between cryptocurrencies in both the pre- and post-COVID-19 eras was introduced into the mean equation outlined below. The mean equation applies the VAR (1)—BEKK GARCH-M (1,1) method developed by Engle and Kroner (1995). The mean equation used in this study was as follows:

$$\begin{aligned} Rt_t &= \mu + \sum_{i=1}^{p} \Phi_i R_{t-1} + \delta_i VIX_t + \varepsilon_t \\ \varepsilon_t &= H_t^{1/2} \eta_t , \end{aligned} \tag{1}$$

where $Rt_{t+1} = \left[Rt_{t+1}^{BTC} \;\; Rt_{t+1}^{ETH} \, Rt_{t+1}^{BNB} \;\; Rt_{t+1}^{ADA} \, Rt_{t+1}^{DOGE} \;\; Rt_{t+1}^{XLM} \, Rt_{t+1}^{XRP} \;\; Rt_{t+1}^{LITE} \right]'$ shows the returns on eight variables[1] and Φ represents the estimated parameters of the lagged variables in the Rt_{t+1} mean equations with an 8 × 8 matrix, $\Phi = \begin{pmatrix} \Phi_{11} & \Phi_{12} \\ \Phi_{21} & \Phi_{22} \end{pmatrix}$. While $\mu = [\mu_1, \mu_2]'$ reveals a vector of constant coefficients in the mean equation, δ represents the effects of VIX as an exogeneous variable on the returns of cryptocurrencies. Moreover, $\eta_t = \left[\eta_t^{BTC} \;\; \eta_t^{ETH} \, \eta_t^{BNB} \;\; \eta_t^{ADA} \, \eta_t^{DOGE} \;\; \eta_t^{XLM} \, \eta_t^{XRP} \;\; \eta_t^{LITE} \right]'$ is a vector of independently and identically distributed random noises corresponding to each return variable in the mean equation. The H matrix is defined below.

The conditional variances of the above equation are estimated using VAR (1)-BEKK GARCH (1, 1). The algebraic presentation of VAR (1)-BEKK GARCH (1, 1) is as follows:

$$H_t = \Upsilon\Upsilon' + A'\varepsilon_{t-1}\varepsilon_{t-1}'A + B'H_{t-1}B \tag{2}$$

where H is a 4 × 4 matrix representing the conditional variance–covariance matrix, Υ is a 4 × 4 upper triangular constant coefficient matrix, and A and B are each an 8 × 8 matrix of parameters where

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[1] Each commodity's return is computed as $Rt_{i,t+1} = 100 * \ln \left(\frac{P_{i,t+1}}{P_{i,t}} \right)$, where P states the cryptocurrencies.

$\Upsilon = (C + \Gamma VIX_t)$. The constant term, Υ, is incorporated to reflect the effects of the VIX on the time-dependent conditional variance–covariance of the considered cryptocurrencies. The matrices A and B show the estimators expressing the impacts of shocks and volatilities, respectively. The estimation of the VAR (1)-BEKK GARCH (1, 1) model was estimated using the quasi-maximum likelihood (QML) method. The present study evaluated the BEKK–MGARCH model compared to other approaches, including the vectorized conditional variance matrices (VECH) stacking method, the constant conditional correlation (CCC) model, and the dynamic conditional correlation (DCC) model. The BEKK model was chosen because of its ability to incorporate asymmetric information flows from diverse data sources (Rahman and Serletis, 2012; Salisu and Oloko, 2015; Urak and Bilgic, 2023; Urak, Bilgic, Bozma, et al., 2022). The BEKK–MGARCH model's superiority in capturing asymmetric information flows makes it particularly suitable for analyzing the complex dynamics of cryptocurrency markets. This model's flexibility allows a more nuanced understanding of how shocks and volatilities propagate across cryptocurrencies, potentially revealing hidden patterns in their interdependencies. Furthermore, the incorporation of the VIX into the model provides valuable insights into how broader market sentiment and volatility influence the cryptocurrency ecosystem. The BFGS[2] algorithm was used to determine the parameters by maximizing Equation (2).

Data and Preliminary Analysis

This study examines the interconnections in cryptocurrency volatility during the period of uncertainty precipitated by COVID-19. The study's approach not only captures the complex dynamics within the cryptocurrency market, but also explores its relationship with traditional financial markets. By analyzing these interconnections during the COVID-19 pandemic, this research may uncover unique patterns of volatility transmission and market behavior under extreme conditions. This comprehensive analysis could provide valuable insights into risk management strategies and portfolio diversification in the evolving landscape of digital assets. This study delves into the intricate web of relationships among cryptocurrency volatilities during the tumultuous period of the COVID-19 pandemic. By examining these interconnections, this research seeks to uncover the underlying dynamics that drive price fluctuations in the cryptocurrency market, particularly under conditions of extreme uncertainty. This broader perspective allows a more comprehensive understanding of how different asset classes respond to global crises and how their volatilities may influence one another. These findings could reveal new insights into the role of cryptocurrencies in the global financial ecosystem, particularly during times of market stress. Furthermore, the results of this comprehensive analysis may have significant implications for risk management strategies and portfolio diversification techniques. As the landscape of digital assets continues to evolve, understanding the complex interplay of volatilities across markets becomes increasingly crucial for investors and financial institutions seeking to navigate the challenges and opportunities presented by cryptocurrencies. The data utilized in the study were taken daily from the DataStream database for this reason. The daily data between 2018 and 2022 were split into two sections, that is, before and after COVID-19 (January 2020), to examine the effect of this change. Pre-COVID-19 data spanned January 2018 through December 2019, whereas post-COVID-19 data spanned January 2020 through March 2022. Before COVID-19, there were 503 observations, and after COVID-19, there were 571 observations. Moreover, 250 observations for the ARCH model and 500 observations for the GARCH model would be sufficient, according to Hwang and Valls Pereirra (2006). In managing portfolio risks, volatility plays an important role. The GARCH model is a widely used estimator of the volatility of equity returns (Nghi and Kieu, 2021). In this situation, the data are sufficient, and robust error terms are not required. Analyses were performed using series logarithmic returns. Table 1 presents some descriptive statistics of the return series.

Table 1. Descriptive Statistics of Returns (Full Sample)

Statistics	BTC	ETH	BNB	ADA	DOGE	XLM	XRP	LITE
Mean	0.108	0.126	0.364	0.041	0.262	-0.080	-0.086	-0.060
Std. Dev.	4.780	6.279	7.102	7.300	20.347	7.284	7.360	6.353
Skewness	-1.224	-0.876	-0.392	-0.181	0.404	0.445	0.036	-0.666
Kurtosis	12.812	9.838	14.031	5.116	325.339	9.338	13.569	7.179
Jarque-Bera	7607.773 (0.000)	4465.079 (0.000)	8829.965 (0.000)	1176.272 (0.000)	4732230 (0.000)	3934.245 (0.000)	8232.358 (0.000)	2384.204 (0.000)
Q (6)	10.634 (0.100)	16.693 (0.010)	16.323 (0.012)	14.438 (0.025)	150.713 (0.000)	6.719 (0.347)	4.672 (0.586)	6.966 (0.323)
LM-Arch (6)	2.584	4.331	12.781	6.010	119.249	6.168	4.628	4.383

[2] BFGS stands for the Broyden–Fletcher–Goldfarb–Shanno algorithm.

	(0.017)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ADF	-22.297 (0.000)	-21.982 (0.000)	-22.765 (0.000)	-21.783 (0.000)	-31.826 (0.000)	-22.273 (0.000)	-23.270 (0.000)	-22.741 (0.000)
KPSS	0.122	0.105	0.086	0.180**	0.040	0.070	0.048	0.086
Correlation								
ETH	0.802							
BNB	0.650	0.675						
ADA	0.711	0.762	0.612					
DOGE	0.226	0.220	0.211	0.231				
XLM	0.651	0.700	0.588	0.795	0.240			
XRP	0.600	0.661	0.578	0.701	0.206	0.761		
LITE	0.791	0.808	0.654	0.730	0.227	0.680	0.659	-

*Note: *, ** and *** are statistically significant at 10%, 5% and 1% respectively. Q is statistics of Ljung-Box for the null hypothesis of no autocorrelation for a series. The LM-statistic tests a set of series for multivariate ARCH effects.*

BNB had the highest return at 0.364%, according to the descriptive statistics for January 2018–March 2022. The series with the highest volatility was Dogecoin, according to the unconditional variance calculated using the standard deviations for the period under study. Dogecoin has undergone significant gains and losses due to the amount of speculation directed toward it before and after COVID-19. Because of its extreme volatility and, in particular, Elon Musk’s tweets, Dogecoin (Shahzad et al., 2022b) was one of the top eight most actively traded cryptocurrencies. The least volatile cryptocurrency among those examined was BTC. ETH followed BTC. Significantly, these two coins dominate the market in terms of market capitalization, which is the reason for their low volatility.

The leptokurtic (fat-tail) distribution of the investigated series is indicated by the kurtosis coefficient, which also raises the possibility that the ARCH effect may be present. When the skewness coefficient is examined, all series—aside from DOGE, XLM, and XRP—show negative skewness. In finance theory, negative skewness denotes the probability that investors will experience negative returns rather than positive returns from their investments. Additionally, the Ljung–Box statistic value reveals that ETH, BNB, ADA, and DOGE are autocorrelated (i.e., their returns are determined by prior behavior), while the Jarque–Bera statistic shows that the return series is not normally distributed. All Bitcoin return series display increased volatility (heteroskedasticity) in their temporal dimensions, demonstrating that their residual squares are not constant but change over time, regardless of whether individual series exhibit ARCH effects.

Table 1 also displays the correlation indices between return variables. Thus, the positive link between cryptocurrency returns is notable. ETH and LITE had the strongest positive correlation (0.808). Consequently, the correlation between BTC and ETH was 0.80. In other words, a change of one unit in either of the two variables’ standard deviations will result in a change of 0.802 in the linear standard deviation of the other variable. The return series was discovered to be unit root free by the ADF and KPSS unit root tests.

Empirical Findings and Discussion

While many factors can affect the price of cryptocurrencies, the stability of the global economy is one of the most important. When the global economy is unstable, investors seek safer alternatives to invest their money. They often turn to assets that are considered safer, such as gold or government bonds. However, in recent years, the cryptocurrency market has become a popular alternative (Gherghina et al., 2024). The relationship between the cryptocurrencies with the highest volume in the pre- and post-COVID-19 periods is shown by the mean and variance equation in tables 2 and 3. Each series can be represented in the equation as a return since the logarithmic differences of the series are employed. Using information criteria, such as Akaike, Schwartz, and Hannan Quin, the ideal lag lengths in the mean equations are shown to be 1. Table 2 depicts that during the pre-COVID-19 time frame, BTC's lag in its own return had a detrimental impact on the returns of other coins. Dogecoin, a very well-known and speculative coin in the cryptocurrency market, has a one-period lagged return that raises the returns of other currencies and its own. In other words, BTC increases by 9.7%, and ETH climbs by 11.2% for a 100% gain in the one-period lagged return of the DOGE currency. Another interesting fact is that only BNB, XLM, and XRP were statistically significantly impacted by VIX hikes. BNB falls by 5.8% when VIX rises 100%, yet XLM and XRP fall by 3.4% and 3.5%, respectively. Giannellis (2022) investigated the commitment of the cryptocurrency market during the COVID-19 pandemic. According to the analysis, the rise in VIX increased the interconnectivity of Bitcoin returns. Table 3's parameter results for the average equation's values during the post-COVID-19 period show that, except for ADA, DOGE, and XLM, BTC's one-period lagged return value has a positive impact on other coins' returns. By beginning to re-energize the market, the rise in BTC's return influences other coins (Karaömer, 2022; Oyewola et al., 2022; Khan et al., 2022).The lagged return values of cryptocurrencies are revealed to have a detrimental impact on other cryptocurrencies when the parameter values in the average equation are generally studied. This condition affects both the pre-COVID-19 era and the post-COVID-19 era. The observed result underscores that cryptocurrencies exhibit first-moment (average) volatility. Investors demonstrate a preference for divestment from the market when returns decrease as returns increase, which may potentially lead to adverse consequences for the market from which the investor withdraws, resulting in a decline in returns. Lahmiri and Bekiros (2020) used a comparative analysis to examine how the COVID-19 epidemic affected the stock market and cryptocurrency marketplaces. Unlike the stock market, the Bitcoin market showed greater sensitivity to the epidemic. This suggests a high level of volatility and instability. The effect of Twitter/X investor participation on cryptocurrencies during the COVID-19 outbreak was studied by Bouteska et al. (2023). This analysis demonstrated the potential spillover effects among cryptocurrencies by highlighting the varied impacts of the pandemic on each one. Su and Kao (2022) inspected how the COVID-19 pandemic affected the equity, oil, gold, foreign exchange, and cryptocurrency markets. They discovered sizable volatility spillover effects in most markets, indicating an interconnection. The pandemic substantially influenced cryptocurrencies during a brief financial panic, according to Luxmana and Oktafiyani (2022).

Tables 2 and 3 present volatility transitivity across crypto markets using the VAR–BEKK MGARCH model in the pre- and post-COVID-19 periods. First, if we analyze the pre-COVID-19 period in Table 2, short-term uncertainties in the BTC market have a statistically significant effect on the conditional variance of BTC (a11 = -0.451). In other words, good and bad news in the BTC market increases the uncertainty of BTC. Although increased risk in financial markets is not perceived as positive, the risk and return are inversely proportional. In cryptocurrencies, the risk is high; however, the return can also be quite high. Simultaneously, short-term shocks in the BTC market increase the conditional variance (long-term uncertainty) of the ETH market (a21 = -0.111). Conversely, good or bad news from the BTC market decreases uncertainty in the ADA, XLM, XRP, and LITE markets. This shows that short-term uncertainty in the BTC market prolongs long-term uncertainty in its own market and the ETH market while offsetting uncertainty in the ADA (a41 = -0.184), XLM (a61 = -0.380), XRP (a71 = -0.117), and LITE (a81 = -0.152) markets. In contrast, short-term shocks in the ETH market reduce the long-term uncertainty in BTC (a12 = -0.142) and DOGE (a52 = -0.291), while increasing the long-term volatility in ADA (a42 = 0.207) and XRP (a72 = 0.180). Ji et al. (2019) found that Bitcoin, with its high market capitalization and dominant position in the cryptocurrency market, is the main contributor to volatility spillovers in the cryptocurrency market. Sinlapates and Chancharat (2023) examined volatility spillovers between Bitcoin and other major cryptocurrencies. Their study revealed evidence of volatility spillover effects between all 11 cryptocurrency pairs and showed that shocks and volatility are transmitted between Bitcoin and other cryptocurrencies. Katsiampa (2019) investigated the volatility dynamics of two major cryptocurrencies: Bitcoin and Ether. The study found evidence of the interdependence and sensitivity of conditional volatility and correlation with major news events, showing the impact of Bitcoin's volatility on Ether's volatility. Harb et al. (2022) examined the volatility interdependence between cryptocurrencies and the stock and bond markets. Their study found evidence of volatility spillovers across cryptocurrencies, with Bitcoin transmitting shocks to other cryptocurrencies.

Continuing from Table 2, long-run uncertainties in Bitcoin have a statistically significant and positive effect on the long-run uncertainties of other cryptocurrencies. This may indicate BTC's dominance of cryptocurrencies. As evidence, the effect of the long-run volatility of other cryptocurrencies on BTC is either statistically significant, or the parameter values are very near zero. These findings support the studies of Ji et al. (2019), Sinlapates and Chancharat (2023), and Xu et al. (2022).

Table 2. VAR, GARCH-BEKK model- Pre-Covid 19 Era

Estimate	BTC	ETH	BNB	ADA	DOGE	XLM	XRP	LITE
Conditional mean equation								
$\Gamma_{i1,t-1}$	-0.063* (0.036)	-0.209*** (0.043)	-0.125** (0.054)	-0.121** (0.051)	-0.058 (0.04)	-0.104** (0.051)	-0.090** (0.044)	-0.210*** (0.045)
$\Gamma_{i2,t-1}$	-0.096*** (0.030)	-0.047 (0.042)	-0.105** (0.052)	-0.121** (0.051)	-0.16*** (0.038)	-0.155*** (0.046)	-0.146*** (0.044)	-0.111*** (0.04)
$\Gamma_{i3,t-1}$	0.002 (0.020)	-0.03 (0.025)	0.021 (0.035)	0.006 (0.032)	-0.03 (0.027)	-0.041 (0.032)	-0.003 (0.027)	0.008 (0.029)

$\Gamma_{i4,t-1}$	-0.023 (0.022)	-0.085*** (0.029)	-0.112*** (0.034)	-0.05 (0.033)	0.045 (0.03)	-0.143*** (0.031)	-0.180*** (0.027)	0.031 (0.031)
$\Gamma_{i5,t-1}$	0.097*** (0.017)	0.112*** (0.022)	0.038 (0.029)	0.09*** (0.025)	0.043 (0.031)	0.101*** (0.026)	0.070*** (0.024)	0.131*** (0.024)
$\Gamma_{i6,t-1}$	-0.04* (0.021)	0.081*** (0.028)	0.028 (0.037)	0.125*** (0.031)	-0.045* (0.025)	0.108*** (0.03)	0.060** (0.025)	0.064** (0.03)
$\Gamma_{i7,t-1}$	0.041* (0.022)	0.018 (0.028)	-0.121*** (0.042)	-0.097*** (0.032)	0.081*** (0.03)	-0.091*** (0.033)	0.042 (0.032)	0.002 (0.033)
$\Gamma_{i8,t-1}$	0.104*** (0.024)	0.145*** (0.029)	0.319*** (0.041)	0.16*** (0.036)	0.099*** (0.032)	0.240*** (0.038)	0.208*** (0.032)	0.066** (0.033)
Constant (μ)	-0.198* (0.114)	-0.263* (0.143)	-0.196 (0.187)	-0.471*** (0.159)	-0.395*** (0.133)	-0.558*** (0.167)	-0.468*** (0.144)	-0.256* (0.154)
VIX	0.012 (0.013)	-0.011 (0.017)	-0.058** (0.024)	-0.037** (0.018)	-0.018 (0.016)	-0.034* (0.019)	-0.035** (0.019)	0.005 (0.017)
Conditional variance equation								
c_{i1}	1.407*** (0.118)							
c_{i2}	2.316*** (0.185)	0.908*** (0.137)						
c_{i3}	0.590 (0.378)	2.238*** (0.21)	1.141*** (0.386)					
c_{i4}	2.678*** (0.216)	0.903*** (0.277)	0.661*** (0.189)	1.522*** (0.111)				
c_{i5}	1.339*** (0.214)	0.785*** (0.195)	-1.130*** (0.183)	-0.130 (0.178)	-0.512** (0.250)			
c_{i6}	2.298*** (0.204)	0.566** (0.261)	0.343 (0.264)	-0.454** (0.190)	0.503 (0.329)	0.000 (0.731)		
c_{i7}	1.731*** (0.152)	0.174 (0.172)	-0.340** (0.169)	-0.069 (0.120)	0.264* (0.157)	0.000 (0.260)	0.000 (0.133)	
c_{i8}	2.739*** (0.194)	0.559** (0.255)	0.684*** (0.182)	1.248*** (0.136)	0.206 (0.151)	0.000 (0.192)	0.000 (0.178)	0.000 (0.127)
a_{i1}	0.451*** (0.042)	0.111** (0.049)	-0.012 (0.067)	-0.184*** (0.049)	0.060 (0.063)	-0.380*** (0.060)	-0.117** (0.049)	-0.152*** (0.049)
a_{i2}	-0.142*** (0.035)	0.0410 (0.052)	-0.118 (0.075)	0.207*** (0.05)	-0.291*** (0.055)	-0.009 (0.057)	0.180*** (0.047)	0.046 (0.051)
a_{i3}	0.082*** (0.02)	0.136*** (0.032)	0.463*** (0.035)	-0.074** (0.038)	0.075** (0.033)	0.122*** (0.041)	0.086*** (0.03)	0.050 (0.034)
a_{i4}	0.053** (0.027)	0.180*** (0.037)	0.466*** (0.052)	0.223*** (0.054)	0.429*** (0.038)	0.249*** (0.048)	0.151*** (0.04)	-0.049 (0.036)
a_{i5}	-0.063* (0.034)	-0.022 (0.046)	0.023 (0.043)	0.072 (0.049)	0.928** (0.044)	0.021 (0.043)	0.024 (0.043)	0.107 (0.048)
a_{i6}	-0.014 (0.023)	0.060* (0.037)	-0.297*** (0.039)	-0.051 (0.038)	-0.114*** (0.037)	0.148*** (0.040)	0.064** (0.033)	-0.058* (0.035)
a_{i7}	0.128*** (0.037)	-0.035 (0.047)	0.326*** (0.060)	-0.013 (0.058)	-0.319*** (0.046)	0.303*** (0.060)	-0.039 (0.049)	-0.006 (0.047)
a_{i8}	-0.171*** (0.028)	-0.183*** (0.039)	-0.609*** (0.058)	0.155*** (0.04)	-0.215*** (0.045)	-0.077*** (0.043)	-0.125*** (0.038)	0.329*** (0.042)
b_{i1}	0.824*** (0.030)	0.125*** (0.036)	0.265*** (0.057)	0.387*** (0.033)	-0.062 (0.039)	0.445*** (0.044)	0.223*** (0.032)	0.289*** (0.032)
b_{i2}	0.004 (0.021)	0.563*** (0.037)	-0.498*** (0.064)	-0.093*** (0.031)	0.027 (0.038)	-0.005 (0.039)	-0.324*** (0.033)	0.072** (0.032)
b_{i3}	0.023 (0.021)	-0.060** (0.026)	0.252*** (0.042)	-0.033 (0.028)	0.062** (0.027)	-0.14*** (0.033)	0.145*** (0.022)	0.012 (0.027)
b_{i4}	0.052** (0.022)	0.119*** (0.026)	0.069 (0.055)	0.521*** (0.035)	0.031 (0.035)	-0.246*** (0.034)	0.066** (0.027)	-0.46*** (0.022)
b_{i5}	0.029 (0.021)	-0.217*** (0.022)	-0.142*** (0.03)	-0.031 (0.029)	0.528*** (0.026)	0.059** (0.027)	-0.111*** (0.021)	-0.023 (0.024)
b_{i6}	-0.069*** (0.024)	0.015 (0.027)	0.237*** (0.051)	0.247*** (0.033)	0.099*** (0.032)	0.819*** (0.026)	-0.026 (0.036)	0.223*** (0.035)
b_{i7}	0.035** (0.014)	0.131*** (0.016)	0.024 (0.045)	0.193*** (0.016)	-0.006 (0.027)	0.246*** (0.029)	0.981*** (0.022)	0.263*** (0.019)
b_{i8}	-0.018 (0.02)	0.09*** (0.021)	0.597*** (0.051)	-0.327*** (0.027)	0.063* (0.037)	-0.310*** (0.042)	-0.116*** (0.025)	0.548*** (0.025)
VIX_{i1}	0.070*** (0.010)							
VIX_{i2}	0.122*** (0.018)	0.122*** (0.012)						
VIX_{i3}	0.139*** (0.030)	0.023 (0.037)	0.206*** (0.025)					
VIX_{i4}	0.073*** (0.022)	0.142*** (0.016)	0.046*** (0.016)	0.006 (0.013)				

VIX_{i5}	0.119*** (0.020)	0.103*** (0.020)	0.006 (0.018)	0.011 (0.019)	0.054*** (0.017)			
VIX_{i6}	0.051** (0.021)	0.113*** (0.020)	0.094*** (0.022)	0.020 (0.021)	-0.060*** (0.018)	0.000 (0.028)		
VIX_{i7}	0.121*** (0.022)	0.170*** (0.017)	0.001 (0.017)	0.012 (0.017)	-0.045*** (0.016)	0.000 (0.025)	0.000 (0.019)	
VIX_{i8}	0.019 (0.018)	0.092*** (0.016)	0.008 (0.019)	0.010 (0.015)	0.021 (0.015)	0.000 (0.022)	0.000 (0.020)	0.000 (0.011)
Diagnostic tests								
Q(6)	4.508 [0.608]	5.777 [0.448]	7.445 [0.281]	5.190 [0.519]	4.516 [0.607]	5.810 [0.444]	1.815 [0.935]	1.780 [0.938]
McLeod-Li (6)	0.993 [0.985]	7.833 [0.250]	3.392 [0.758]	3.124 [0.793]	15.244 [0.018]	2.029 [0.917]	7.889 [0.246]	4.101 [0.663]
MV Q-statistic (6)	364.671 [0.753]							
MV Q^2-statistic (6)	379.828 [0.550]							
MV ARCH-statistic (6)	18666.44 [0.000]							
MV $ARCH^2$-statistic (6)	28205.63 [0.000]							

*Note: *, ** and *** are statistically significant at 10%, 5% and 1% respectively. Q is statistics of Ljung-Box for the null hypothesis of no autocorrelation for a series in question on standardized residuals. McLeod-li tests for nonlinearity under the null hypothesis of no ARCH effect for a series in question on standardized residuals. MV Q-statistic and MV Q^2-statistic are Hosking's multivariate portmanteau Q-statistics on the standardized and standardized squared residuals, respectively in diagnosing the null hypothesis of no autocorrelation in all series for lag one through specified lags. The LM-statistic tests a set of series for multivariate ARCH effects. Under the null hypothesis that the series are mean zero, not serially correlated with a fixed covariance matrix.*

The parameter results for the mean and variance equations for the post-COVID-19 period are displayed in Table 3. Interestingly, when tables 2 and 3 are compared, the parameter's value changes from negative to positive during the post-COVID-19 era, despite the one-period lagged value of BTC having a negative impact on ETH during the pre-COVID-19 period. Similar circumstances are visible in the impact of ETH's historical return on other cryptocurrencies. COVID-19's effects on the makeup and dynamics of the cryptocurrency market were examined by Hong and Yoon (2022). Their study showed that throughout the pandemic, the network structure and collective behavior of market assets changed. In the pre- and post-COVID-19 periods, there were noticeable changes in both short-term shocks and long-term volatilities.

Following Kroner and Ng (1998) and Kroner and Sultan (1993), analyses of the hedge ratio and optimal portfolio weight were employed to determine the appropriate allocation of investors' portfolio weights in the pre- and post-COVID-19 periods to enhance understanding of this phenomenon. According to Kroner and Sultan (1993), the ideal hedging ratio reduces the risk associated with the choice of the portfolio $\beta_t^{i,j} = \frac{h_t^{i,j}}{h_t^{j,j}}$, where $h_t^{i,j}$ and $h_t^{j,j}$ have already been defined. One can hedge a long position in asset i by taking a short position in asset j.

Table 3. VAR, GARCH-BEKK model- Post Covid-19 Era

Estimate	**BTC**	**ETH**	**BNB**	**ADA**	**DOGE**	**XLM**	**XRP**	**LITE**
Conditional mean equation								
$\Gamma_{i1,t-1}$	0.024 (0.035)	0.118*** (0.041)	0.126*** (0.042)	-0.025 (0.048)	-0.167** (0.084)	-0.141*** (0.047)	0.074* (0.045)	0.096*** (0.032)
$\Gamma_{i2,t-1}$	0.069 (0.023)	0.059** (0.03)	0.139*** (0.031)	0.207*** (0.034)	0.269*** (0.063)	0.220*** (0.027)	0.147*** (0.024)	0.153*** (0.02)
$\Gamma_{i3,t-1}$	-0.010 (0.02)	-0.071*** (0.026)	-0.049* (0.029)	0.034 (0.026)	-0.002 (0.043)	0.022 (0.026)	0.053** (0.024)	-0.048*** (0.019)
$\Gamma_{i4,t-1}$	-0.080*** (0.019)	-0.133*** (0.025)	-0.042* (0.026)	-0.113*** (0.035)	0.095* (0.05)	-0.09*** (0.03)	-0.108*** (0.029)	-0.125*** (0.02)
$\Gamma_{i5,t-1}$	-0.009* (0.005)	-0.011* (0.006)	-0.016*** (0.005)	-0.027*** (0.008)	-0.175*** (0.028)	-0.024*** (0.006)	-0.019*** (0.006)	-0.005 (0.006)
$\Gamma_{i6,t-1}$	0.048* (0.028)	0.073** (0.036)	-0.041 (0.033)	0.027 (0.042)	-0.181*** (0.06)	0.079* (0.048)	0.087* (0.049)	0.099*** (0.034)

$\Gamma_{i7,t-1}$	0.018 (0.021)	0.038 (0.028)	0.009 (0.028)	-0.015 (0.032)	-0.071 (0.06)	0.026 (0.035)	0.036 (0.038)	0.017 (0.026)
$\Gamma_{i8,t-1}$	-0.116*** (0.023)	-0.162*** (0.028)	-0.231*** (0.027)	-0.220*** (0.035)	0.145* (0.078)	-0.229*** (0.032)	-0.337*** (0.028)	-0.261*** (0.023)
Constant (μ)	0.388*** (0.107)	0.524*** (0.13)	0.144 (0.134)	0.262 (0.168)	-0.164 (0.215)	0.023 (0.161)	0.032 (0.145)	0.321*** (0.106)
VIX	-0.051*** (0.013)	-0.076*** (0.016)	-0.022 (0.016)	-0.065*** (0.019)	-0.119*** (0.029)	-0.073*** (0.019)	-0.049*** (0.017)	-0.005 (0.014)
Conditional variance equation								
c_{i1}	-0.280 (0.106)							
c_{i2}	0.062 (0.189)	0.923*** (0.110)						
c_{i3}	-0.030 (0.144)	0.439*** (0.105)	-0.168 (0.143)					
c_{i4}	-0.757*** (0.271)	2.187** (0.115)	-0.635*** (0.278)	0.000 (0.838)				
c_{i5}	-1.274*** (0.335)	-0.495* (0.264)	-0.382 (0.437)	0.000 (0.604)	0.000 (0.422)			
c_{i6}	-0.513** (0.263)	1.885 (0.134)	-0.245 (0.312)	0.000 (0.455)	0.000 (0.181)	0.000 (0.134)		
c_{i7}	-0.578** (0.260)	1.967 (0.131)	-0.442* (0.256)	0.000 (0.61)	0.000 (0.128)	0.000 (0.142)	0.000 (0.126)	
c_{i8}	-0.028 (0.215)	1.693*** (0.113)	-0.318 (0.226)	0.000 (0.621)	0.000 (0.192)	0.000 (0.129)	0.000 (0.183)	0.000 (0.106)
a_{i1}	0.057 (0.040)	0.028 (0.022)	-0.053** (0.025)	0.011 (0.016)	-0.011*** (0.005)	0.223*** (0.023)	-0.043** (0.022)	-0.145*** (0.025)
a_{i2}	-0.059 (0.058)	0.060** (0.030)	-0.131*** (0.034)	0.122*** (0.021)	-0.012 (0.007)	0.156*** (0.030)	0.212*** (0.027)	-0.279*** (0.038)
a_{i3}	-0.097 (0.060)	-0.268*** (0.041)	0.284*** (0.038)	0.063*** (0.023)	-0.017*** (0.006)	0.039 (0.030)	0.165*** (0.027)	-0.105*** (0.038)
a_{i4}	-0.204*** (0.069)	0.213*** (0.041)	-0.141*** (0.041)	0.266*** (0.036)	-0.022*** (0.008)	0.174*** (0.035)	0.222*** (0.037)	-0.466*** (0.050)
a_{i5}	0.431*** (0.101)	-0.336*** (0.062)	0.126** (0.058)	-0.337*** (0.049)	0.850*** (0.030)	0.455*** (0.075)	1.349*** (0.071)	-3.697*** (0.106)
a_{i6}	-0.297** (0.065)	0.254*** (0.041)	0.151*** (0.044)	0.161*** (0.028)	-0.031*** (0.007)	0.334*** (0.035)	0.102** (0.039)	-0.570*** (0.049)
a_{i7}	-0.193*** (0.071)	0.157*** (0.045)	-0.061* (0.042)	0.203*** (0.030)	-0.026*** (0.007)	0.207*** (0.038)	0.516*** (0.045)	-0.639*** (0.046)
a_{i8}	-0.160*** (0.063)	0.076*** (0.034)	-0.103*** (0.037)	0.125*** (0.025)	-0.006 (0.007)	0.128*** (0.034)	0.263*** (0.034)	-0.281*** (0.039)
b_{i1}	0.858*** (0.017)	0.033*** (0.017)	0.022* (0.010)	-0.034*** (0.010)	-0.017*** (0.006)	0.092*** (0.015)	-0.030*** (0.009)	0.017 (0.015)
b_{i2}	0.048** (0.026)	0.913*** (0.015)	0.108*** (0.014)	-0.035*** (0.013)	-0.027*** (0.009)	-0.145*** (0.014)	-0.116*** (0.014)	0.143*** (0.023)
b_{i3}	-0.156*** (0.021)	0.057*** (0.027)	0.911*** (0.016)	-0.080*** (0.013)	-0.022*** (0.008)	0.112*** (0.017)	-0.050*** (0.010)	0.095*** (0.019)
b_{i4}	0.045** (0.020)	0.114*** (0.022)	0.110*** (0.019)	0.807*** (0.014)	-0.034** (0.010)	0.028 (0.025)	-0.072*** (0.013)	-0.123*** (0.027)
b_{i5}	-0.044 (0.084)	0.325*** (0.075)	0.033 (0.050)	0.035 (0.060)	-0.012 (0.015)	0.286*** (0.064)	0.067* (0.048)	0.068 (0.068)
b_{i6}	-0.037 (0.027)	0.623*** (0.023)	0.005 (0.024)	-0.161*** (0.019)	-0.002 (0.009)	0.799*** (0.018)	0.073*** (0.020)	-0.436*** (0.030)
b_{i7}	0.118*** (0.024)	0.249*** (0.014)	0.074*** (0.020)	-0.173*** (0.013)	-0.025*** (0.009)	-0.146*** (0.020)	0.902*** (0.014)	-0.134*** (0.031)
b_{i8}	0.094*** (0.030)	0.012 (0.023)	-0.032** (0.018)	-0.161*** (0.016)	-0.015* (0.009)	0.281** (0.013)	-0.113*** (0.014)	0.843*** (0.020)
VIX_{i1}	0.128*** (0.009)							
VIX_{i2}	0.164*** (0.014)	-0.014 (0.010)						
VIX_{i3}	0.196*** (0.013)	-0.032** (0.012)	0.002 (0.014)					
VIX_{i4}	0.201** (0.017)	-0.010 (0.015)	0.014 (0.018)	0.000 (0.022)				
VIX_{i5}	0.049 (0.034)	0.038 (0.034)	0.007 (0.035)	0.000 (0.047)	0.000 (0.041)			
VIX_{i6}	0.152 (0.017)	-0.009 (0.014)	-0.003 (0.018)	0.000 (0.025)	0.000 (0.016)	0.000 (0.013)		
VIX_{i7}	0.169 (0.017)	-0.011 (0.015)	0.011 (0.016)	0.000 (0.02)	0.000 (0.013)	0.000 (0.013)	0.000 (0.012)	
VIX_{i8}	0.188***	-0.005	0.003	0.000	0.000	0.000	0.000	0.000

	(0.015)	(0.012)	(0.013)	(0.019)	(0.014)	(0.014)	(0.013)	(0.012)
Diagnostic tests								
Q(6)	4.829 [0.565]	7.009 [0.319]	12.332 [0.054]	7.712 [0.259]	11.803 [0.066]	3.552 [0.736]	8.341 [0.214]	10.928 [0.090]
McLeod-Li (6)	1.144 [0.979]	3.172 [0.786]	3.660 [0.722]	5.790 [0.447]	0.415 [0.998]	3.200 [0.783]	2.630 [0.853]	3.284 [0.772]
MV Q-statistic (6)	370.739 [0.677]							
MV Q^2-statistic (6)	402.458 [0.248]							
MV ARCH-statistic (6)	17519.16 [0.000]							
MV $ARCH^2$-statistic (6)	43498.24 [0.000]							

*Note: *, ** and *** are statistically significant at 10%, 5% and 1% respectively. Q is statistics of Ljung-Box for the null hypothesis of no autocorrelation for a series in question on standardized residuals. McLeod-li tests for nonlinearity under the null hypothesis of no ARCH effect for a series in question on standardized residuals. MV Q-statistic and MV Q^2-statistic are Hosking's multivariate portmanteau Q-statistics on the standardized and standardized squared residuals, respectively in diagnosing the null hypothesis of no autocorrelation in all series for lag one through specified lags. The LM-statistic tests a set of series for multivariate ARCH effects. Under the null hypothesis that the series are mean zero, not serially correlated with a fixed covariance matrix.*

The ideal hedge ratios between cryptocurrencies throughout the pre-COVID-19 and post-COVID-19 periods are displayed in Table 4. According to the empirical results, a trader held a short position in ETH with $1.06 in exchange for a long position in BTC with $1 during the pre-COVID-19 time frame. After COVID-19, the quantity of short positions decreased to $1.03. In contrast to a DOGE short position of 77 cents versus a long position of $1 in BTC in the pre-COVID-19 era, the DOGE short position climbed to 85 cents in the post-COVID-19 time frame. The findings suggest that the optimal hedging strategies for cryptocurrency portfolios have shifted in response to the COVID-19 pandemic. This shift in hedging strategies may be attributed to increased market volatility and uncertainty during the pandemic. Investors likely seek to minimize risk exposure by adjusting their short and long positions across cryptocurrencies. Further research is needed to determine the long-term implications of these changes on cryptocurrency portfolio management and risk mitigation strategies. Investors and traders may need to adjust their hedging ratios between Bitcoin, Ethereum, and Dogecoin to maintain effective risk management in the evolving cryptocurrency market. This implies that the pandemic has altered the relationships between these cryptocurrencies, potentially affecting their relative values and risk profiles. Correspondingly, market participants should regularly reassess and update their hedging strategies to account for these changing dynamics in the post-COVID-19 era. Figures A.3 and A.4 of Table 4 illustrate that investors' behavior varied between the pre-COVID-19 and post-COVID-19 periods. However, under the premise that an investor must choose a portfolio that minimizes risk levels without diminishing expected price returns, Kroner and Ng (1998) demonstrated how market participants—namely, the producers and consumers of a commodity—can protect themselves from volatility. Following Kroner and Ng (1998), the optimal portfolio weight can be obtained as follows:

$$w_t^{i,j} = \frac{h_t^{j,j} - h_t^{i,j}}{h_t^{i,i} - 2h_t^{i,j} + h_t^{jj}},\ i = BTC, ETH, BNB, ADA, DOGE, XLM, XRP, LITE$$

$$w_t^{i,j} = \begin{cases} 0, & if\ \ w_t^{i,j} < 0 \\ w_t^{i,j}, & if\ \ 0 \le w_t^{i,j} \le 1 \\ 1, & if\ \ w_t^{i,j} > 1 \end{cases} \tag{3}$$

In Equation (5), $w_t^{i,j}$ shows the optimal portfolio weighting between cryptocurrencies, $h_t^{j,j}$ the conditional variance of cryptocurrency j, $h_t^{i,j}$ the conditional covariance between cryptocurrencies i and j, and h_t^{i} the conditional variance of cryptocurrency i. Table 5 displays the optimal portfolio weights calculated for the pre- and post-COVID-19 periods.

Table 4. Hedge Ratio Between Crypto Currencies

	Pre-Covid Era	Post-Covid Era

	Mean	St Dev	Min	Max	Mean	St Dev	Min	Max
BTC/ETH	1.06	0.24	0.04	1.91	1.03	0.21	0.28	2.97
BTC/BNB	0.91	0.29	0.05	2.38	0.87	0.28	-0.03	1.92
BTC/ADA	1.12	0.26	-0.28	1.94	1.02	0.25	0.26	4
BTC/DOGE	0.77	0.56	-4.39	3.87	0.85	2.37	-48.65	10.63
BTC/XLM	1.03	0.31	-0.06	2.6	0.97	0.29	-0.27	3.62
BTC/XRP	0.92	0.26	-0.11	2.11	0.95	0.38	0.12	6.03
BTC/LITE	1.02	0.24	-0.2	1.53	1.15	0.21	0.52	3.54
ETH/BTC	0.63	0.15	0.08	1.28	0.62	0.14	0.11	1.28
ETH/BNB	0.72	0.24	-0.44	1.87	0.72	0.21	-0.46	1.43
ETH/ADA	0.94	0.2	-0.2	1.73	0.87	0.19	0.34	1.92
ETH/DOGE	0.54	0.45	-1.82	3.11	0.75	1.83	-35.82	7.26
ETH/XLM	0.83	0.26	-0.78	1.94	0.78	0.22	-0.29	2.16
ETH/XRP	0.79	0.2	0.23	1.9	0.80	0.29	-0.09	2.82
ETH/LITE	0.83	0.19	-0.17	1.19	0.87	0.13	0.31	1.81
BNB/BTC	0.45	0.14	0.02	1.15	0.50	0.18	0	1.18
BNB/ETH	0.59	0.18	-0.15	1.07	0.70	0.24	-0.17	1.98
BNB/ADA	0.63	0.24	-0.53	1.29	0.77	0.28	-0.21	2.61
BNB/DOGE	0.46	0.36	-2.04	2.23	0.63	1.99	-40.38	9.44
BNB/XLM	0.62	0.24	-0.13	1.56	0.73	0.25	-0.12	2.45
BNB/XRP	0.52	0.19	-0.03	1.33	0.74	0.36	-0.32	4.06
BNB/LITE	0.59	0.21	-0.6	1.08	0.75	0.24	-0.16	2.23
ADA/BTC	0.49	0.12	-0.6	0.91	0.43	0.13	0.13	0.96
ADA/ETH	0.69	0.16	-0.04	1.4	0.61	0.12	0.25	0.94
ADA/BNB	0.56	0.22	-0.64	1.51	0.57	0.2	-0.44	1.51
ADA/DOGE	0.52	0.34	-1.29	2.78	0.63	1.59	-30.78	6.45
ADA/XLM	0.82	0.15	0.37	1.74	0.73	0.15	0.03	1.36
ADA/XRP	0.70	0.16	0.2	1.26	0.68	0.24	0.1	1.89
ADA/LITE	0.70	0.14	0.14	1.01	0.67	0.14	0.28	1.29
DOGE/BTC	0.50	0.26	-0.36	1.23	0.28	0.27	-0.08	1.26
DOGE/ETH	0.60	0.38	-0.74	1.44	0.34	0.31	-0.24	1.2
DOGE/BNB	0.58	0.34	-1.1	1.57	0.34	0.32	-0.28	1.28
DOGE/ADA	0.71	0.35	-0.37	1.69	0.40	0.37	-0.39	1.79
DOGE/XLM	0.67	0.40	-1.45	2.11	0.41	0.37	-0.46	1.39
DOGE/XRP	0.60	0.32	-0.32	1.35	0.38	0.36	-0.59	1.8
DOGE/LITE	0.61	0.30	-0.34	1.27	0.38	0.33	-0.23	1.37
XLM/BTC	0.47	0.13	-0.3	0.85	0.44	0.16	-0.23	1.06
XLM/ETH	0.64	0.19	-0.08	1.22	0.59	0.18	-0.16	1.05
XLM/BNB	0.57	0.23	-0.47	1.29	0.60	0.23	-0.05	1.35
XLM/ADA	0.85	0.15	0.27	1.38	0.78	0.17	0.05	1.5
XLM/DOGE	0.51	0.36	-2.27	2.16	0.63	1.65	-29.64	5.79
XLM/XRP	0.70	0.17	0.23	1.38	0.81	0.22	-0.04	1.99
XLM/LITE	0.65	0.17	0.01	1.38	0.67	0.16	-0.08	1.09
XRP/BTC	0.55	0.16	-0.33	1.21	0.41	0.17	0.04	1.04
XRP/ETH	0.80	0.20	0.13	1.56	0.55	0.18	-0.08	1.07
XRP/BNB	0.63	0.20	-0.26	1.8	0.53	0.21	-0.18	1.12
XRP/ADA	0.94	0.17	0.44	1.66	0.68	0.22	0.11	1.47
XRP/DOGE	0.57	0.39	-1.88	2.77	0.60	1.65	-31.04	6.9
XRP/XLM	0.91	0.20	0.43	1.7	0.74	0.17	-0.02	1.33
XRP/LITE	0.74	0.19	0.08	1.73	0.66	0.16	0.10	1.08
LITE/BTC	0.56	0.13	-0.23	0.95	0.57	0.13	0.18	1.23
LITE/ETH	0.78	0.18	-0.05	1.47	0.73	0.14	0.22	1.39
LITE/BNB	0.67	0.26	-0.69	2.03	0.65	0.21	-0.41	1.37
LITE/ADA	0.88	0.16	0.1	1.31	0.8	0.2	0.32	2.09
LITE/DOGE	0.58	0.36	-0.35	3.52	0.71	1.22	-17.82	6.35
LITE/XLM	0.78	0.21	0.01	1.83	0.75	0.2	-0.08	1.63
LITE/XRP	0.69	0.19	0.11	1.46	0.8	0.25	0.15	1.91

In Table 5, a pre-COVID-19 investor put $88 in BTC and $12 in ETH into a portfolio of $100 worth of Bitcoin and Ethereum. This condition transformed to $90 in BTC and $10 in ETH in the post-COVID-19 era. The ideal portfolio weight between BTC/DOGE increased from 0.73 in the pre-COVID-19 period to 0.87 in the post-COVID-19 period, which is a notable difference. Buyers invested more in BNB in the post-COVID-19 time period than in the pre-COVID-19 period, considering the position between ETH/BNB. The ideal portfolio weights for several cryptocurrencies are displayed in Table 5. This shift in portfolio weights suggests that Bitcoin gained relative importance compared to Dogecoin following the COVID-19 pandemic. The recommendation to increase investments in Binance Coin (BNB) post-COVID-19 indicates a potential change in market dynamics or investor sentiment toward this cryptocurrency. These findings underscore the importance of regularly reassessing and adjusting cryptocurrency portfolio allocations in response to significant global events and changing market conditions. While Bitcoin gained relative importance compared to Dogecoin following the COVID-19 pandemic, Binance Coin (BNB) emerged as a recommended investment option, highlighting the diverse impacts of the global event on different cryptocurrencies and the need for dynamic portfolio management strategies. The implications of these findings are significant for cryptocurrency investors and portfolio managers. The observed shift in portfolio weights and investment recommendations suggests that the COVID-19 pandemic substantially impacted the cryptocurrency market, altering the relative importance and potential returns of digital assets. This underscores the need for investors to remain vigilant and adaptable in their investment strategies, particularly during global crises or significant market events. The increased relative importance of Bitcoin compared to Dogecoin post-pandemic implies that investors may have gravitated toward more established and widely recognized cryptocurrencies during uncertain times. This could indicate a flight to perceived safety or stability within the volatile cryptocurrency market. The recommendation to increase investment in Binance Coin (BNB) suggests that some cryptocurrencies may have benefited from the changing market dynamics brought about by the pandemic. This implies that investors should not only focus on the most prominent cryptocurrencies but also be open to emerging opportunities in the market. These findings emphasize the importance of dynamic portfolio management in the cryptocurrency space. Investors and fund managers should be prepared to reassess and rebalance their portfolios regularly, considering global events, market trends, and the evolving landscape of digital assets. This may involve developing more sophisticated risk management strategies and staying informed about both macroeconomic factors and cryptocurrency-specific developments. Furthermore, the diverse impacts of the pandemic on cryptocurrencies highlight the need for a nuanced understanding of the crypto market. Investors should recognize that global events may affect digital assets differently and that what applies to one cryptocurrency may not necessarily hold true for another. Finally, these findings imply that successful cryptocurrency investment strategies in the post-COVID era may require a more agile, informed, and diversified approach, with a keen eye on both established players, such as Bitcoin, and emerging opportunities, similar to Binance Coin.

Table 5. Optimal Portfolio Weight Between Crypto Currencies

	Pre-Covid Era				Post-Covid Era			
	Mean	St Dev	Min	Max	Mean	St Dev	Min	Max
BTC/ETH	0.88	0.24	0	1	0.90	0.20	0	1
BTC/BNB	0.86	0.17	0	1	0.82	0.22	0	1
BTC/ADA	0.94	0.14	0.1	1	0.94	0.12	0.14	1
BTC/DOGE	0.73	0.26	0	1	0.87	0.20	0	1
BTC/XLM	0.91	0.15	0.17	1	0.91	0.13	0	1
BTC/XRP	0.81	0.24	0	1	0.89	0.14	0	1
BTC/LITE	0.90	0.19	0.05	1	0.97	0.14	0	1
ETH/BNB	0.62	0.23	0	1	0.52	0.25	0	1
ETH/ADA	0.79	0.25	0	1	0.79	0.19	0.03	1
ETH/DOGE	0.43	0.31	0	1	0.73	0.29	0	1
ETH/XLM	0.67	0.27	0	1	0.68	0.21	0	1
ETH/XRP	0.47	0.33	0	1	0.69	0.22	0	1
ETH/LITE	0.59	0.32	0	1	0.69	0.22	0	1
BNB/ADA	0.57	0.22	0	1	0.69	0.27	0	1
BNB/DOGE	0.39	0.29	0	1	0.71	0.31	0	1
BNB/XLM	0.53	0.25	0	1	0.61	0.27	0	1
BNB/XRP	0.40	0.22	0	1	0.65	0.26	0	1
BNB/LITE	0.43	0.23	0	1	0.59	0.28	0	1

ADA/DOGE	0.31	0.31	0	1	0.63	0.35	0	1
ADA/XLM	0.40	0.32	0	1	0.42	0.27	0	1
ADA/XRP	0.22	0.28	0	1	0.45	0.29	0	1
ADA/LITE	0.29	0.26	0	1	0.34	0.24	0	1
DOGE/XLM	0.64	0.30	0	1	0.35	0.35	0	1
DOGE/XRP	0.55	0.31	0	1	0.36	0.33	0	1
DOGE/LITE	0.57	0.31	0	1	0.32	0.33	0	1
XLM/XRP	0.29	0.29	0	1	0.54	0.28	0	1
XLM/LITE	0.38	0.26	0	1	0.42	0.22	0	1
XRP/LITE	0.55	0.30	0	1	0.39	0.25	0	1

Conclusion

This empirical investigation has unveiled intricate dynamics within the cryptocurrency market, specifically in the periods preceding and following the COVID-19 pandemic. An examination of the mean and variance equations has provided valuable insights into the behavior of prominent cryptocurrencies. Before the pandemic, Bitcoin (BTC) assumed a pivotal position, exerting significant sway over the performance of various cryptocurrencies, including Ethereum (ETH), DOGE, ADA, XLM, XRP, and LITE. The presence of inherent short-term uncertainties within the BTC market exerted a notable impact, leading to elevated conditional variance in both the BTC and ETH. Nevertheless, the presence of these uncertainties alleviated the uncertainties associated with ADA, XLM, XRP, and LITE, thereby underscoring the intricate interplay between risk and return dynamics within the realm of cryptocurrencies.

Our research provides empirical evidence that substantiates the widely accepted hypothesis that Bitcoin (BTC) exerts substantial influence on the cryptocurrency market. This phenomenon is apparent in the discernible influence it exerts on the enduring uncertainties surrounding alternative cryptocurrencies. This discovery aligns with prior academic investigations that emphasized the substantial impact of BTC on the wider cryptocurrency ecosystem. The post-pandemic era witnessed notable shifts in established dynamics characterized by their paradigmatic nature. An essential modification observed is the alteration of parameter values, signifying a transformation from a previously negative correlation between the lagged returns of BTC and ETH to a positive one. This transition underscores the notable capacity of cryptocurrency markets to adjust and develop in response to external factors, as exemplified by the repercussions of the pandemic. The findings of our analysis demonstrate congruence with prior scholarly investigations, thereby emphasizing the intricate interdependencies within the cryptocurrency sector. The practical implications of these findings hold significant importance for investors aiming to optimize the efficiency of their investment portfolios. The analysis conducted in this study provides evidence in favor of the notion that traders should contemplate the adoption of both long and short positions, particularly cryptocurrencies, as a strategy to proficiently mitigate risk. Furthermore, empirical evidence has demonstrated a significant relationship between the allocation of portfolio weights and the dynamic nature of market conditions, underscoring the importance of employing adaptive investment strategies.

In conclusion, the cryptocurrency market remains a dynamic and rapidly evolving domain. The study's empirical findings offer significant insights that are valuable to both investors and scholars. The aforementioned findings underscore the considerable influence exerted by the BTC and the consequences arising from external disturbances, such as the pandemic. Additionally, they emphasized the importance of employing flexible investment strategies to effectively navigate the intricacies of this exceedingly volatile environment. Considering the continuous development of the cryptocurrency domain, it is imperative for the academic community to engage in additional research and inquiry to comprehend and exploit its intrinsic capacities. This endeavor will yield advantages for both individual and institutional investors. The study found that the pandemic significantly affected the cryptocurrency market, thereby changing the market's dynamics. This suggests that regulators must be prepared to adapt their policies in response to changing market conditions. Moreover, there is a lack of understanding about cryptocurrencies among both investors and regulators. This suggests that regulators should promote research and education about cryptocurrencies to improve their understanding of the risks and benefits of this new asset class.

The results of this study can guide policy makers in several ways. In particular, it offers insights into investing in cryptocurrencies in monitoring and managing risks amid uncertainties such as COVID-19.
However, this paper has its limitations. First, eight cryptocurrencies were analyzed by this study. The scope of this study can be expanded by analyzing more cryptocurrencies. Second, the period considered was between 2018 and 2022, when COVID-19 and VIX's effects had yet to be determined. In addition, the effects

of events that cause global uncertainties, such as the Russia–Ukraine War, can be analyzed. Third, different perspectives can be obtained using machine learning and artificial intelligence techniques as analytical methods. Finally, future studies could examine the effects of COVID-19 and VIX on assets besides cryptocurrencies.

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Figure A1. Prices of Cryptocurrencies

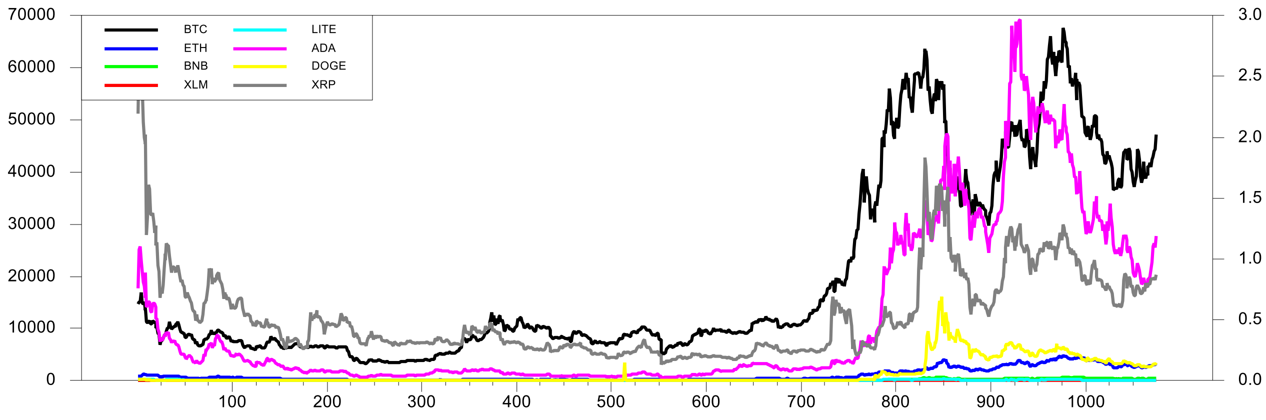


Figure A2. Returns of Cryptocurrencies

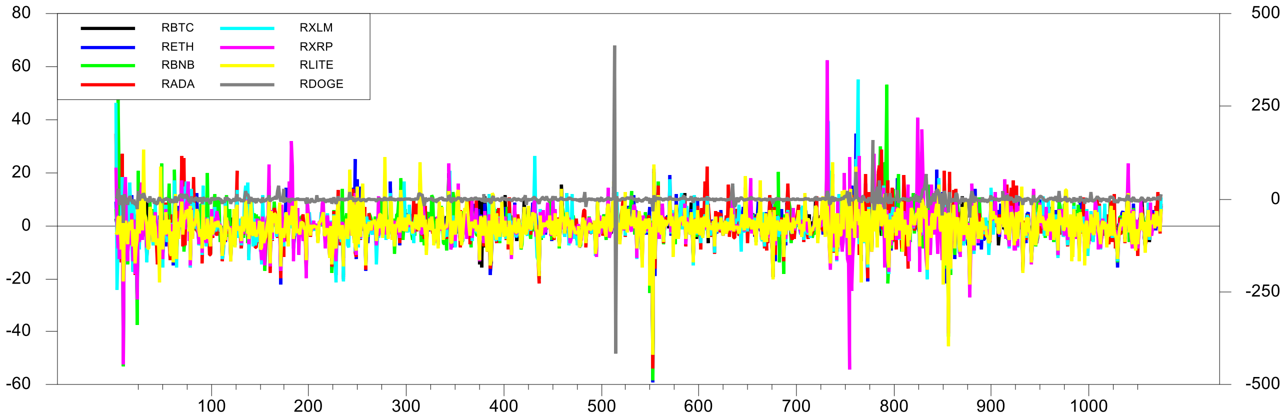
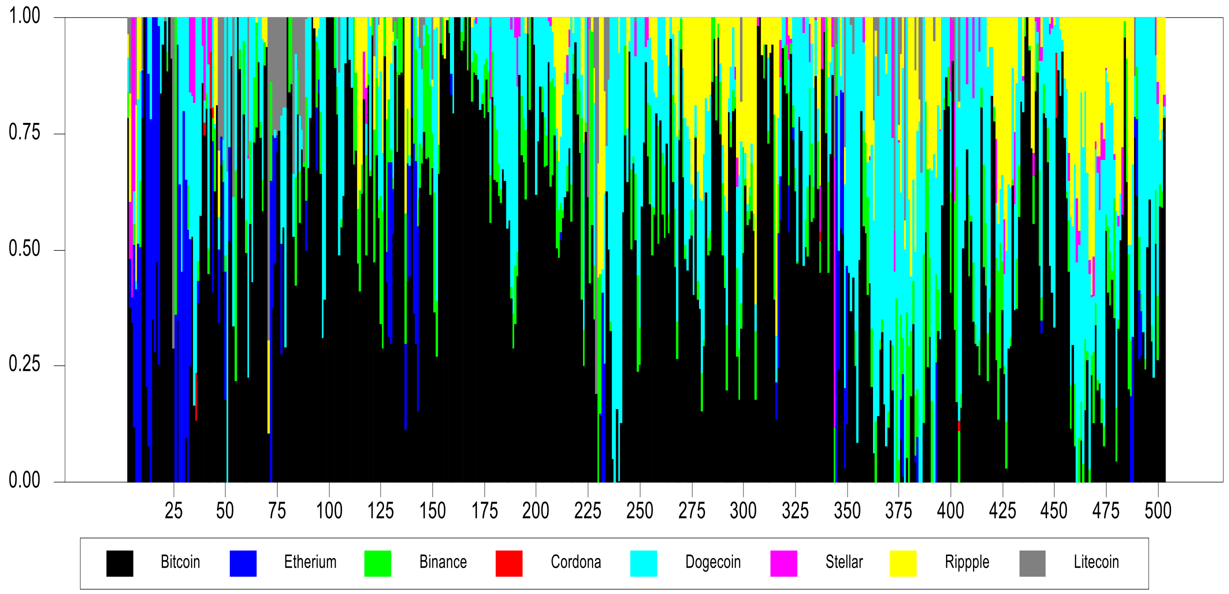
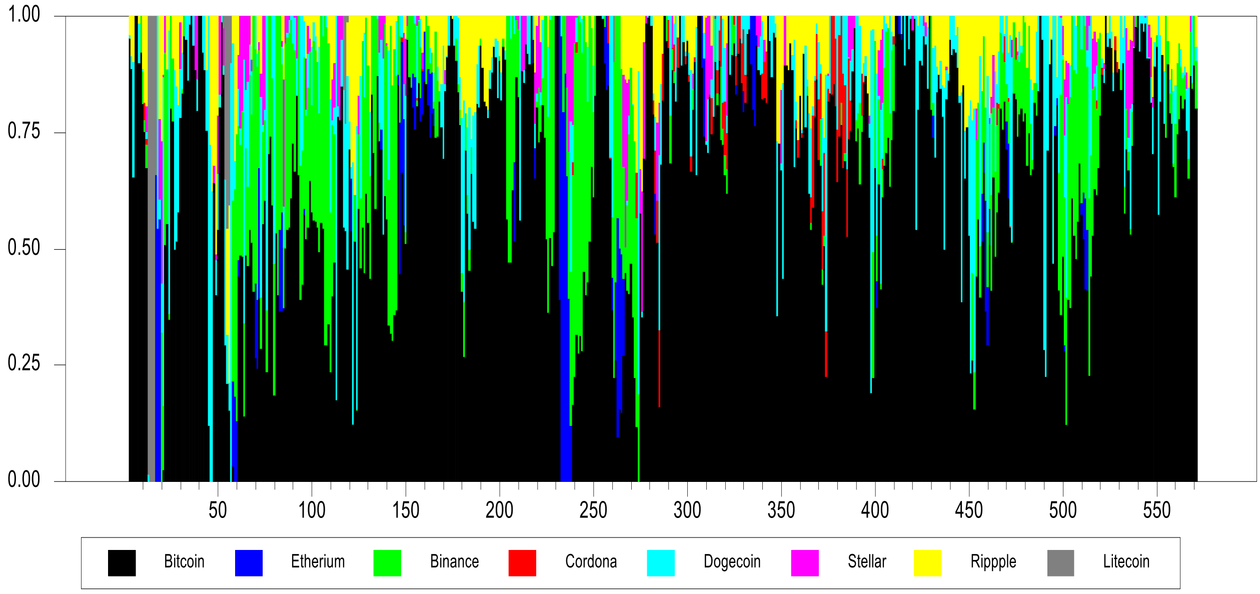


Figure A3. Long-position Portfolio Weight Pre-Covid



Long-position Portfolio Weights

Figure A4. Long-position Portfolio Weight Post-Covid-19



Long-position Portfolio Weights