Volatility Interdependence Between Cryptocurrencies, Equity, and Bond Markets

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Abstract
This paper investigates (i) the return-volatility spillover between Bitcoin, Ethereum, Ripple, and Litecoin, (ii) the interdependence between cryptocurrencies’ volatility and the US equity and bond markets’ volatility, and (iii) the impact of the Covid-19 outbreak on the cryptocurrencies’ return-volatility. A two-step estimation approach is considered where Univariate General Autoregressive Conditional Heteroskedastic models are estimated to model the volatility of the four cryptocurrencies then a Simultaneous Equation Model is estimated to model the interconnection between the cryptocurrency volatilities, the US equity and bond markets’ volatility, and Covid-19 outbreak. We show that return-volatility spillovers exist among Bitcoin, Ethereum, and Litecoin while Ripple is the main transmitter of shocks. We find that the cryptocurrency market is detached from the US stock market but not from the US bond market. Finally, we show that a high economic and financial uncertainty in the US stock market due to pandemic outbreaks affects the price of Litecoin, Bitcoin, and Ethereum. However, shocks are short-lived. Our findings have practical implications;
as the evidence of volatility spillovers among cryptocurrencies and their relative isolation from the majority of mainstream assets should be factored into the valuation and portfolio diversification strategies of investors. In crisis times such as those induced by Covid-19, investors who seek protection from downward movements in bond markets could benefit from taking a position in Ethereum. Policymakers can also rely on our findings to time their intervention to stabilize markets and control uncertainties inherent to stressful periods.

**Keywords** Cryptocurrencies · Volatility spillover · GARCH-SEM · Structural breaks · Pandemics

### 1 Introduction

Cryptocurrencies emerged almost 20 years ago as an alternative to token money and experienced stunning growth. Despite the exponential increase in the number of businesses that accept payments in Bitcoin, there is still no consensus on whether cryptocurrencies satisfy the three functions of money: medium of exchange, unit of account, and store of value (Polasik et al., 2015). Whether they are currencies or non-conventional financial assets, investors became recently highly interested in their use. In fact, according to the Coin Market Cap website,1 in April 2021, the market capitalization of Bitcoin and Ethereum increased to $1.1 trillion and $250 billion respectively. Thus, Bitcoin and Ethereum together represent almost 60% of the total estimated cryptocurrency market capitalization. With Ripple and Litecoin, they represent the top four most traded cryptocurrencies (Coin Market Cap, June 2022).

Many studies in the literature investigated the behavior and the interconnectedness of cryptocurrencies. Some studies used VAR models and Granger causality analysis to show that there are return spillovers among cryptocurrencies (Antonakakis et al., 2019). Other studies estimated GARCH models to show that volatility spillovers exist between cryptocurrencies (Beneki et al., 2019; Katsiampa et al., 2019a, 2019b; Katsiampa, 2019a, 2019b). Further studies investigated both return and volatility spillover (Chaim & Laurini, 2019; Corbet et al., 2018; Ji et al., 2019; Katsiampa, 2019a; Koutmos, 2018). Prior research mostly examined the hedging property, safe haven, and diversification characteristics of Bitcoin vis-à-vis stock market and bond market indices (Bouri et al., 2017a, b). However, the literature fails to account for three aspects of the financial markets. *First*, one can expect cryptocurrency market volatility to depend on investors’ fear. When investors’ fear is high then cryptocurrency markets face an increase in volatility. Hence, investors’ expected volatility of the equity and bond markets affects the volatility in the cryptocurrency market. *Second*, the stock market volatility attributed to exogenous shocks like infectious disease outbreaks (e.g. Covid-19 pandemic) has an impact on the volatility of cryptocurrencies. *Third*, the presence of structural breaks while modelling volatility in GARCH frameworks would render the impact of exogenous shocks on cryptocurrency volatility permanent and GARCH models unstable. Accounting for structural breaks in the models is necessary.

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1 www.coinmarketcap.com.
to capture the true mechanisms that drive changes in the data. Failing to recognize them can lead to invalid conclusions and inaccurate policy recommendations. In our paper, we try to fill this gap and address those shortcomings.

Given that cryptocurrencies are highly volatile (Gkillas & Katsiampa, 2018), it is informative to study, on one side, their inter- and intra-volatility dynamics and on the other side, their interconnection with equity and bond markets’ uncertainties. It is also important to investigate the direction of the interdependence in their volatility and the impact of stock market uncertainties caused by exogenous shocks like the Covid-19 outbreak on their volatility. This would help investors and portfolio managers in (i) understanding the interlinkages between cryptocurrencies’ volatilities and their detachment or not from financial markets’ volatilities, (ii) predicting their volatility behaviors in the highly controversial cryptocurrency market, and (iii) identifying the dominant and satellite cryptocurrencies. High interconnection between two cryptocurrencies implies that they cannot be selected simultaneously to increase the diversification of an investment portfolio. Moreover, a dominant currency is a market leader that would spill over to other cryptocurrencies.

We consider a two-step estimation approach. First, we model cryptocurrency volatilities by estimating different GARCH models while accounting for structural breaks. We adopt a comparative approach to select the GARCH model that best fits our data. We use the Iterated Cumulative Sums of Squares (ICSS) algorithm proposed by Inclán and Tiao (1994) to test for structural breaks in the unconditional variance. Second, we estimate a Simultaneous Equation Model (SEM) to investigate the spillover effect between and within cryptocurrency volatilities. We include three exogenous variables in the SEM: (i) the US stock market volatility measured by the VIX index, (ii) the US bond market volatility measured by the VXTLT index and (iii) the daily Infectious Disease Equity Market Volatility Tracker (EMVID) recently developed by Baker et al. (2020) that accounts for stock market volatility stemming from epidemic and diseases outbreaks.

Overall, our analysis contributes in four ways to the academic debate about the cryptocurrency market. First, it analyzes the dynamics of volatility spillovers among cryptocurrencies. Second, our sample period spans from the first of January 2016 till February 26, 2021, covering different peaks of the Covid-19 outbreak that led to financial markets turbulences (Gupta et al., 2021; Shahzad et al., 2021). Hence, we account for stress periods caused by the first global economic and financial disruption that hit the world since the launch of cryptocurrencies. Third, it investigates the potential diversification role of cryptocurrencies against conventional assets, more particularly, stocks and bonds (Akhtaruzzaman et al., 2021; Conlon & McGee, 2020; Conlon et al., 2020; Corbet et al., 2020; Maasoumi & Wu, 2021; Yoshino et al., 2021). Fourth, it tackles an econometric issue that has been ignored in most of the literature. To the best of our knowledge, only few studies accounted for structural breaks in cryptocurrency dynamics, and these studies covered the period before the Covid-19 outbreak (Abakah et al., 2020; Ji et al., 2018).

The empirical findings are three-fold. First, we identify an instantaneous positive bidirectional volatility spillover effect between Ethereum and Litecoin, and between Ethereum and Bitcoin. We also find an instantaneous negative bidirectional volatility spillover effect between Bitcoin and Litecoin. Interestingly, the magnitude of the
bidirectional spillover is higher for large cryptocurrencies. A unidirectional instantaneous volatility spillover effect runs from Ripple to the three other cryptocurrencies with a positive impact on Bitcoin and Litecoin, and a negative effect on Ethereum. Overall, the identified volatility spillover effects are short-lived showing that shocks in the cryptocurrency market are transitory with a half-life shock of fewer than two days. Second, the US stock market volatility does not affect any of the volatilities of the studied cryptocurrencies, while deviations in the bond market cause Bitcoin and Litecoin to deviate from equilibrium and Ethereum to converge to equilibrium. Interestingly, the two biggest cryptocurrencies in terms of market capitalization (Bitcoin and Ethereum) react in opposite directions to the volatility in the US bond market. Third, we show that high economic and financial uncertainty in the US market due to pandemic outbreaks can push the price of Litecoin and Bitcoin to converge back to equilibrium while it causes Ethereum to diverge from its equilibrium.

The paper is organized into six sections. Section 2 reviews the related literature with hypotheses development. Section 3 describes the data and the preliminary tests. Section 4 presents the methodology. Section 5 discusses the main empirical findings and shows a robustness check exercise. Section 6 stands for the conclusion.

2 Literature Review and Hypotheses Development

Investigating the interconnectedness between the cryptocurrency market and traditional financial markets (equity and bonds) contributes to understanding the information transmission mechanism. It also provides valuable information for market participants, which would help them in the selection of their portfolios. The Modern Portfolio Theory (MPT), pioneered by Markowitz (1952), argues that investors can achieve their best results by identifying an optimal mix of the high risk-high return assets and low risk-low return assets based on an assessment of their individual risk tolerance. The key component of this theory is diversification. The latter is measured by the correlation between different assets included in the investment portfolio. Cryptocurrencies have been increasingly accepted by the traditional financial sector as a legitimate asset class. Such large acceptance combined with the maturity of the cryptocurrency market increased the correlation between traditional financial markets and cryptocurrencies leading to a decline in their safe haven properties (Urquhart & Lucey, 2022). Additionally, the cryptocurrency market is one of the core financial platforms where financial investors target higher returns, especially during uncertain periods such as the Covid-19 outbreak. In this regard, Dempsey et al. (2022) assess the characteristics of risk and return of cryptocurrencies from an investment perspective through the fundamental asset pricing and portfolio theory. Interestingly, cryptocurrencies outperform all traditional portfolios and their risk remained stable during the pandemic. This is attributed to the wider use of cryptocurrencies from institutional investors and governments and the availability of several other cryptocurrencies that reduce the dominance of Bitcoin. As the cryptocurrency market has matured, the

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2 https://theconversation.com/crypto-crash-market-volatility-is-testing-investor-will-but-crypto-enthusiasts-still-see-a-future-for-the-asset-class-185339. Accessed on June 24, 2022.
impact of investors’ attention on price becomes a unique characteristic of the crypto market (Liu & Tsyvinski, 2021). Smales (2022) finds that there is a positive relation between investor attention and returns for the largest 20 cryptocurrencies. However, the increase in investors’ attention is also associated with greater volatility and less liquidity.

### 2.1 Return and Volatility Spillovers Among Cryptocurrencies

The growing literature that addresses market linkages among cryptocurrencies employs several approaches, mainly Vector Autoregressive (VAR) models, Generalized Autoregressive Conditional Heteroskedastic (GARCH) models, Granger causality tests, wavelets, and other techniques.

VAR models proposed by Diebold and Yilmaz (2009, 2012, 2014) were widely used on raw return data to study the static and the dynamic interdependence between cryptocurrencies. For instance, Koutmos (2018) examines return and volatility spillovers among Bitcoin and 17 large cryptocurrencies and finds that the connectedness magnitude varies with time. He shows that Bitcoin, Ethereum, Ripple, and Tether are mainly affected by their own return shocks. However, Litecoin is affected by its own shocks and those stemming from other cryptocurrencies. Moreover, he identified Bitcoin as the main transmitter of volatility shocks and Litecoin as the receiver of volatility shocks. Similarly, Corbet et al. (2018) investigate the return and volatility connectedness of Bitcoin, Ripple, and Litecoin, but their findings are not in line with those of Koutmos (2018) as they show that Ripple and Litecoin are affected by return shocks from Bitcoin while the return and volatility spillovers between Ripple and Litecoin are strong. They also show that Litecoin and Ripple have a significant volatility spillover on Bitcoin. Ji et al. (2019) study return and volatility spillovers among six cryptocurrencies (Bitcoin, Ethereum, Ripple, Litecoin, Stellar, and Dash). Consistent with Koutmos (2018), they identify volatility spillovers among the six cryptocurrencies but confirm the centrality of Bitcoin to the network of volatility spillovers. Similarly, Antonakakis et al. (2019) employ a Time-Varying Parameter Factor Augmented VAR model (TVP-FAVAR) to investigate the transmission mechanism among nine leading cryptocurrencies. They show that Bitcoin is the most important transmitter of shocks in the cryptocurrency market, followed by Ethereum. They reveal that connectedness measures among the nine cryptocurrencies exhibit large dynamic variability: periods of high market uncertainty correspond to strong connectedness and vice versa. Ziȩba et al. (2019) also apply VAR models and a Minimum Spanning Tree (MST) to examine the returns of Bitcoin and other leading cryptocurrencies. They find that Bitcoin exhibits a clear segmentation from the other cryptocurrencies.

Other studies considered multivariate GARCH models. For instance, Katsiampa (2019a) uses bivariate and asymmetric diagonal Baba-Engle-Kraft-Kroner (BEKK)-GARCH models with daily price returns to study the volatility co-movement between Bitcoin and Ethereum. She concludes that a bi-directional volatility spillover exists between Bitcoin and Ethereum. On the other hand, Katsiampa (2019b) expands the analysis to study pairwise volatility spillover between Bitcoin, Ethereum, Ripple, Litecoin, and Stellar Lumen. She shows that volatility co-movement exists between each
pair of the six cryptocurrencies. In the same context, Katsiampa et al. (2019b) estimate an asymmetric BEKK-GARCH model with hourly data to investigate conditional volatility dynamics of eight major cryptocurrencies and their volatility co-movements. They demonstrate strong interdependencies among cryptocurrencies with significant asymmetric effects between positive and negative shocks. They also show that Bitcoin is not the dominant player in cryptocurrency markets; although the shocks it transmits to other cryptocurrencies last longer. Benekī et al. (2019) estimate a VAR-BEKK-GARCH model for Ethereum and Bitcoin. They identify unidirectional volatility spillover from Ethereum to Bitcoin. Katsiampa et al. (2019a) estimate three pair-wise bivariate BEKK-GARCH models for Bitcoin, Ethereum, and Litecoin. They detect bi-directional volatility spillovers between Bitcoin and Ethereum and between Bitcoin and Litecoin, and a uni-directional volatility spillover from Ethereum to Litecoin use an AR-GJR-GARCH framework to detect the presence of jumps in the return series of 12 cryptocurrencies. They identify multiple jumps and show that besides Bitcoin, Ethereum and Ripple are important players in the cryptocurrency markets. Smales (2021) follows a DCC-MGARCH model to investigate the return and volatility spillovers across three distinct classes of cryptocurrencies: coins, tokens, and stablecoins. The author finds that the conditional correlations are time-varying especially during the Covid-19 pandemic (peaking due to the sell-off of March 2020). Moreover, he concludes that ARCH and GARCH effects play a crucial role in determining conditional volatility among cryptocurrencies.

Studies such as Bouri et al., (2020a, 2020b, 2020c, 2020d, 2020e) employ a Granger causality framework based on the extended causality test version of Bodart and Candelo (2009) to address volatility linkages among cryptocurrencies. They study the linkage among unexpected volatility or “volatility surprise” of cryptocurrencies and find that in some cases causalities differ between the short and the long runs. They highlight the importance of large cryptocurrencies as major players in the cryptocurrency market.

Aslanidis et al. (2019) use a generalized dynamic conditional correlation model to study the relationship between Bitcoin, Dash, Monero, and Ripple. They reveal that a positive correlation exists among them but differs across time. Only Monero seems to have a stable correlation over time when compared to the other cryptocurrencies. Shi et al. (2020) apply the Multivariate Factor Stochastic Volatility Model (MFSVM) with the Bayesian estimation technique to study the correlations among Bitcoin, Dash, Ethereum, Litecoin, Ripple, and Stellar. They identify a positive correlation in the volatility of the following pairs: Bitcoin-Litecoin, Ethereum-Ripple, Ethereum-Stellar, and Ripple-Dash. They also reveal that Ethereum is connected with Ripple, Dash, and Stellar whereas Bitcoin is only connected to Litecoin.

Several studies apply wavelet-based methods. For instance, Mensi et al. (2019) identify a leading relationship for Bitcoin with Dash, Monero, and Ripple; a lagging relationship for Bitcoin with Ethereum, and an out-of-phase movement for Bitcoin with Litecoin. On the other hand, Kumar and Ajaz (2019) conclude that Bitcoin is the main driver of cryptocurrency prices. Qiao et al. (2020) reveal a positive correlation between Bitcoin and other cryptocurrencies at medium and high frequencies, whereas Bitcoin leads at low frequencies. Furthermore, Qureshi et al. (2020) find that high levels of dependency among cryptocurrencies exist at daily frequency levels.
They show that Ripple and Ethereum are trivial origins of market contagion. Finally, Omane-Adjepong et al. (2019) demonstrate that volatility persistence is highly sensitive to time-scale, return and volatility measures, and regime shift. This suggests that empirical investigation of persistence in markets should consider volatility measures, trading horizons, and switching regimes. In this context, Shahzad et al. (2021) study the daily return spillover among 18 cryptocurrencies under low and high volatility regimes using a Markov regime-switching (MS) vector autoregressive with exogenous variables (VARX) model. They consider three pricing factors and the effect of the Covid-19 outbreak. They show that the patterns of the spillover vary with time. Consistent with contagion during stress periods, return spillover abruptly intensifies following the Covid-19 outbreak, particularly in the high volatility regime. Based on the above discussion, we set the following hypothesis:

\[ H_1 \] There are bi-directional volatility spillovers among Bitcoin, Ethereum, Litecoin, and Ripple.

### 2.2 Hedging, Diversification, and Safe Haven Properties for Cryptocurrencies

Cryptocurrencies’ hedging and safe haven properties were widely examined before the recent pandemic outbreak (Baumöhl, 2019; Baur et al., 2018; Bouri et al., 2017b; Urquhart & Zhang, 2019). For example, Baur et al. (2018) reveal that Bitcoin was neither a hedge nor a safe haven against fiat currencies and the US stock market. Baumöhl (2019) finds that Bitcoin, Ethereum, Ripple, Litecoin, Stellar Lumens, and Nem could offer hedging investment opportunities against foreign exchange currencies. Corbet et al. (2018) support the idea that cryptocurrencies constitute a new investment asset class as they are connected to each other, but disconnected from traditional financial assets.

Similarly, Bouri et al., (2020a, 2020b, 2020c, 2020d, 2020e) study cryptocurrencies’ properties and identify that Bitcoin, Ripple, Litecoin, Stellar, and Monero act as a safe haven against the S&P500 while Ethereum, Dash, and Nem are neither a hedge nor a safe haven against the S&P500. Mariana et al. (2020) find that Ethereum and Bitcoin present short-term safe haven properties against the S&P500 but reveal that Ethereum is possibly a better safe haven than Bitcoin. There is also a rising strand of literature that deals with the diversification role of leading cryptocurrencies, mainly Bitcoin, against conventional assets (fiat currencies, equity, bonds, commodities) during the Covid-19 outbreak (Akhtaruzzaman et al., 2021; Bouri, et al., 2020a, 2020b, 2020c, 2020d, 2020e; Chen et al., 2020; Conlon & McGee, 2020; Conlon et al., 2020; Corbet et al., 2020; Dutta et al., 2020; Goodell & Goutte, 2021; Yoshino et al., 2021).

More recently, few studies examined the connectedness of cryptocurrencies with bond markets such as Anyfantaki et al. (2021), Ciner and Lucey (2022), and Karim et al. (2022). Anyfantaki et al. (2021) show that the inclusion of cryptocurrencies in traditional portfolios is a good diversification option for risk-averse investors; especially during periods of high returns. However, Karim et al. (2022) find that bond markets are neither hedge nor safe haven except for the Dow Jones Global Sukuk index (SKUK) which is a safe haven investment for cryptocurrency indices and offers substantial diversification during the periods of economic fragility.
The inclusion of cryptocurrencies seems to increase the expected return per unit of risk as cryptocurrency returns are expected to have a low or negative correlation with the returns of proxies of traditional asset classes, like bonds and stocks. Hence, we develop the following hypotheses:

\( H_{2a} \) There are volatility spillovers between the US stock markets and the selected cryptocurrencies.

\( H_{2b} \) There are volatility spillovers between the US bond markets and the selected cryptocurrencies.

### 2.3 Cryptocurrencies and Economic and Financial Uncertainty During the COVID-19 Pandemic

During the Covid-19 outbreak, many sectors went dormant for several months, while other sectors were operating below potential. International financial markets also tumbled due to Covid-19 induced uncertainty. Individual investors and portfolio managers who were seeking an alternative asset to hedge the downside risk of conventional financial assets such as stocks and bonds were particularly attracted to cryptocurrencies that seemed to offer interesting investment alternatives for traditional assets during the pandemic. Several studies examined the cryptocurrency connectedness during the pandemic to give investors and portfolio managers insights into how the pandemic affected the behavior of cryptocurrencies. Fasanya et al. (2021), Shahzad et al. (2021), and Polat and Kabakçı Günay (2021) find that volatility spillovers experience significant changes during major market crises. Fasanya et al. (2021) show that the volatility spillover index experiences significant bursts during major market crises. Polat and Kabakçı Günay (2021) find that overall spillover indexes fluctuate in periods of crises and the magnitudes of volatility spillovers from each of the studied cryptocurrencies, except for Ethereum, increased after the Covid-19 announcement. Ethereum seems to catalyze the highest sum of volatility spillovers to other cryptocurrencies followed by Litecoin and Bitcoin before the Covid-19 announcement, whereas Litecoin becomes the largest transmitter of total volatility followed by Bitcoin (89.3%) and Ethereum (88.9%) after the announcement of the pandemic. Hence, we develop the following hypothesis:

\( H_3 \) The economic and financial uncertainty in the US market during the pandemic affects the volatility of the selected major cryptocurrencies.

### 3 Data and Preliminary Tests

Our sample data covers the period from January 1, 2016 to February 26, 2021. Before 2016, the overall market capitalization of cryptocurrencies was stable and fluctuations in cryptocurrency prices were almost inexistent. The cryptocurrencies price series are collected from the Coin Market Cap website (www.coinmarketcap.com), and the daily
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Continuous returns are calculated as follows:

\[ R_t = 100 \times \log \left( \frac{P_t}{P_{t-1}} \right) \]

where \( P_t \) is the closing price in \( t \) and \( P_{t-1} \) is the lagged closing price. We consider the Chicago Board Options Exchange (CBOE) volatility index (VIX) as a proxy of the future volatility of the S&P500 index, and the CBOE 20 + year Treasury bond ETF volatility index (VXTLT) to measure the implied volatility of the US bond market. These two series are extracted from Bloomberg. VIX measures the US financial market risk. It reflects the market expectations for near- and long-term volatility and has been recently used in the literature to assess the relationship between cryptocurrencies and the equity market (Akyildirim et al., 2020; Fakhfekh et al., 2021). VXTLT applies the VIX methodology to the iShares 20 + Year Treasury bonds. It tracks the expected risk attributed to investments in long-term US Treasury bonds with maturities greater than twenty years. Though the relationship between bond and cryptocurrencies market has been previously investigated to assess the diversification properties of cryptocurrencies (Anyfantaki et al., 2021; Ciner & Lucey, 2022), the relationship between cryptocurrencies’ volatilities and bond market volatility has been neglected. The interaction between such forward-looking implied volatility measures and cryptocurrency volatility implies that cryptocurrencies may not be detached from equity and bonds markets. Finally, we opt for the daily Infectious Disease Equity Market Volatility Tracker (EMVID) developed by Baker et al. (2020) to account for stock market volatility caused by pandemic outbreaks. The EMVID is a newspaper-based index that captures stock market volatility in the US attributed to infectious disease outbreaks or policy responses to such outbreaks. The index is re-scaled as follows:

\[ z_t = \ln(e + EMVID_t) \]

Table 12 in the appendix presents the definition of the variables and their sources and Table 1 shows some descriptive statistics related to the return series. The standard deviations range between 4.006 and 7.404 and reflect high variations from the corresponding means. The positive skewness in the case of the returns of the Ripple

|               | Ripple (rip) | Litecoin (lit) | Ethereum (et) | Bitcoin (bit) |
|---------------|-------------|---------------|---------------|-------------|
| Mean          | 0.227       | 0.206         | 0.390         | 0.248       |
| StDev         | 7.011       | 5.630         | 5.932         | 4.006       |
| Skewness      | 2.401 [0.000] | 0.666 [0.000] | −0.240 [0.000] | −0.847 [0.000] |
| Kurtosis      | 39.159 [0.000] | 11.773 [0.000] | 7.783 [0.000] | 13.197 [0.000] |
| JB            | 121865 [0.000] | 10991 [0.000] | 4761 [0.000] | 13860 [0.000] |

(i) StDev stands for standard deviation, (ii) JB is the Jarque-Berra normality test: the null hypothesis is that the return series are normally distributed. (iii) Between brackets are the p-values of the JB test.
Table 2 ADF Unit root test on the log return series

|             | Model 1          | Model 2          |
|-------------|------------------|------------------|
| Ripple (rip)| $-15.428^*$ (5 lags) | $-15.470^*$ (5 lags) |
| Litecoin (lit)| $-15.645^*$ (5 lags) | $-15.708^*$ (5 lags) |
| Ethereum (et)| $-43.052^*$ (0 lag) | $-46.227^*$ (0 lag) |
| Bitcoin (bit)| $-44.051^*$ (0 lag) | $-44.213^*$ (0 lag) |

(i) Model 1 is the ADF regression with neither a constant nor a deterministic trend. (ii) Model 2 is the ADF regression with just a constant. (iii) Between parentheses is the minimum number of lags that eliminates autocorrelation from the errors of the ADF regression. (iv) * denotes rejection of the null hypothesis (non-stationary variable) at a 1% significance level.

(2.401) and the Litecoin (0.666) provides evidence for asymmetric distribution (long tail to the right). Ethereum and Bitcoin have negative skewness (respectively $-0.240$ and $-0.847$) and their distributions are hence skewed to the left. Moreover, the five return series have excess kurtosis (greater than 3) which indicates divergence from normality. The positive kurtosis implies that the distributions of the return series are leptokurtic due to volatility clustering around the mean. The Jarque–Bera test confirms the non-normality of the distribution.

Table 2 summarizes the results of the Augmented Dickey-Fuller (ADF) unit root test (Dickey & Fuller, 1981). As shown in Fig. 1 in the Appendix, the return series do not exhibit a deterministic trend. Therefore, we considered two specifications of the ADF test: (i) neither a constant nor a deterministic trend (model 1) and (ii) a constant (model 2). In both cases, the test rejects the null hypothesis of a unit root at a 1% significance level and confirms the stationarity of the five return time series.

4 Methodology

We adopt in this paper a two-step estimation strategy that has been recently advanced by Hamadi et al. (2017). First, for each return series, we estimate different GARCH models and select the one that best fits the data. The selected model is used to extract the return-volatility. Second, we estimate a Simultaneous Equation Model (SEM) to (i) assess the volatility spillover between the four return series, (ii) evaluate the impact of uncertainties in the stock and bond markets on each cryptocurrency’s return-volatility, and (iii) estimate the impact of economic and financial uncertainties caused by infectious diseases and pandemics like Covid-19 on the return-volatility of cryptocurrencies. Multivariate volatility modelling can be also assessed in the context of a multivariate GARCH. However, the main disadvantage of these models is that the number of unknown coefficients increases rapidly with the increase in the number of variables. Thus, it becomes difficult to maximize the log likelihood function of such models. These models are hence rarely considered when the number of variables exceeds three (De Goeij et al., 2004; Bauwens & Laurent, 2005; Minović, 2009). The SEM approach can potentially overcome the above problem.
4.1 Volatility modeling

Cryptocurrencies are considered assets rather than currencies (Baek & Elbeck, 2015; Dyhrberg, 2016; Glaser et al., 2014), and the cryptocurrency market is highly volatile and subject to speculative attacks (Cheah & Fry, 2015). GARCH-type models are widely used in the literature to estimate the return-volatility of cryptocurrencies (Glaser et al., 2014; Bouoiyour & Selmi, 2015, 2016; Dyhrberg, 2016; Bouri et al., 2017b; Katsiampa, 2019b; Katsiampa et al., 2019a, 2019b; Benek et al., 2019). Rather than pre-specifying the GARCH model, we adopt in this paper a comparative approach and estimate four models from the GARCH family: standard GARCH, EGARCH, GJR-GARCH, and asymmetric EGARCH. We then select the one that best fits the data according to a set of criteria that we will discuss at the end of this section. The standard GARCH model fails to account for asymmetry in the impact of positive and negative shocks. Hence, positive and negative shocks are assumed to have the same effect on conditional volatility. Moreover, it requires the coefficients in the variance equation to be positive. To relax the non-negativity constraint, we consider the EGARCH model proposed by Nelson (1991). The logarithmic construction of the variance equation in the EGARCH ensures that the conditional variance is positive. If asymmetry exists, then negative shocks tend to produce greater volatility than positive shocks. To capture this, we estimate the GJR-GARCH proposed by Glosten et al. (1993) and an asymmetric version of the EGARCH model. These models extend the standard GARCH and EGARCH models by allowing for asymmetry in the variance.

For the four GARCH models, we consider the mean equation to follow an Autoregressive Moving Average (ARMA) process of orders \( p \) and \( q \). According to econometric theory, the autocorrelation (CORRS) of a moving average process is 0 at order \( q + 1 \) and the partial autocorrelation (PARTIALS) of an autoregressive process is 0 at order \( p + 1 \). Hence, the mean equation is given by:

\[
R_t = \rho_0 + \sum_{i=1}^{p} \rho_i R_{t-i} + \sum_{j=0}^{q} \phi_j \varepsilon_{t-j}
\]  

where, \( R_t \) is the daily log return, \( \varepsilon_t \) is the error term with a zero conditional mean and a conditional variance (\( h_t \)) assumed to follow a Student distribution.

Many studies highlight the impacts that jumps in volatility can have on the structure and the dynamics of the volatility modelling (Bouri et al., 2020a, 2020b, 2020c, 2020d, 2020e; Chaim & Laurini, 2018). Neglecting structural breaks increases the degree of persistence in the cryptocurrency market (Abakah et al., 2020). To account for this, we augment the variance equation with dummy variables (\( D_t \)) that capture potential structural changes in the unconditional variance. We use the Iterated Cumulative Sums of Squares (ICSS) algorithm proposed by Inclán and Tiao (1994) to estimate the number and the date of structural breaks in the unconditional variance.

In the case of a standard GARCH(1,1) model, the variance equation is:

\[
h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1} + \sum_{i=1}^{n} d_i D_t
\]  

where, \( h_t \) is the conditional variance, \( \varepsilon_t \) is the error term, \( \alpha_0, \alpha_1, \beta_1 \) are the GARCH coefficients, and \( D_t \) is the dummy variable.
where \( h_t \) and \( h_{t-1} \) represent the conditional variance of the returns in respectively \( t \) and \( t-1 \). \( \alpha_0 \) is the average volatility level. \( \varepsilon^2_{t-1} \) corresponds to the news captured in the lagged error term. \( D_t \) is an intercept dummy variable that takes a value of 1 on the break date and onward and 0 otherwise. The non-negativity constraint on \( \alpha_0, \alpha_1 \) and \( \beta_1 \) is a sufficient condition to have a positive variance. Moreover, \( (\alpha_1 + \beta_1) \) should be less than one so that the GARCH is stable.

In the case of a GJR-GARCH(1,1) model, the variance equation is:

\[
h_t = \alpha_0 + \alpha_1 \varepsilon^2_{t-1} + \beta_1 h_{t-1} + \gamma \varepsilon^2_{t-1} I(\varepsilon_{t-1} < 0) + \sum_{t=1}^{n} d_t D_t
\]

where \( I(\varepsilon_{t-1} < 0) \) is a dummy variable that takes a value of 1 when the errors are negative. If the asymmetry term \( (\gamma) \) is positive, then negative shocks increase the return volatility. The non-negativity constraint and the stability condition described above must also hold.

The conditional variance in the standard EGARCH(1,1) is given by:

\[
\log(h_t) = \alpha_0 + \alpha_1 \frac{|\varepsilon_{t-1}|}{\sqrt{h_{t-1}}} + \beta_1 \log(h_{t-1}) + \gamma \left[ \frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}} \right] + \sum_{t=1}^{m} d_t D_t
\]

where the standardized shocks, \( \eta_t = \frac{\varepsilon_t}{\sqrt{h_t}} \), are independent and identically distributed random variables. \( |\beta_1| < 1 \) is the stability condition. If \( \gamma \) is negative and statistically significant, then negative shocks \( (\varepsilon_{t-1}) \) generate higher volatility than positive shocks. Otherwise, the EGARCH is symmetric and the variance equation becomes:

\[
\log(h_t) = \alpha_0 + \alpha_1 \frac{|\varepsilon_{t-1}|}{\sqrt{h_{t-1}}} + \beta_1 \log(h_{t-1}) + \sum_{t=1}^{m} d_t D_t
\]

We start first by estimating the asymmetric GARCH(1,1) and EGARCH(1,1) models. If the asymmetry term is not significant we then estimate a symmetric GARCH(1,1) and EGARCH(1,1). Second, we check the statistical significance of the coefficients. The best model must have statistically significant coefficients such as the stability condition and the non-negativity constraints are respected. Third, we do some diagnostic tests on the residuals: the standardized errors must be non-autocorrelated and homoskedastic. If this is not the case then a higher order for the GARCH model is estimated: (i) if the standardized errors are heteroskedastic we increase the number of lags of the variance \( (h_{t-1}) \); (ii) if they are autocorrelated we increase the number of lags of the squared errors \( (\varepsilon^2_{t-1}) \). If, given the above, we were unable to select a unique model, we choose the one that satisfies most of the following criteria: Akaike (AIC), Schwartz (BIC) and the Sum Square of the Residuals (SSR) should be minimized while the Likelihood (LL) should be maximized.
4.2 Volatility Spillover

We consider the return-volatility of one cryptocurrency \((\sigma_{et}^t, \sigma_{bit}^t, \sigma_{lit}^t, \sigma_{rip}^t)\) to depend on the current and the lagged return-volatility of the other cryptocurrencies and on its own lagged return-volatility. Return-volatilities are considered to depend on the instantaneous effect of uncertainties caused by infectious diseases \((z_t)\) and the volatility of the US equity and bond markets (respectively \(\sigma_{eqm}^t\) and \(\sigma_{bonds}^t\)). Hence, we estimate the following SEM written in matrix form as per Eq. (6).

\[
BY_t = A_0 + A_1 Y_{t-1} + A_2 X_t + \varepsilon_t
\]

where \(Y_t = (\sigma_{et}^t, \sigma_{bit}^t, \sigma_{lit}^t, \sigma_{rip}^t)'\) is a column vector of endogenous variables, \(X_t = (VIX, VXTLT, z_t)'\) is a vector of exogenous variables. \(A_0, A_1, A_2\) and \(B\) are matrices of coefficients. \(A_1\) and \(B\) are \((4 \times 4)\) matrices such as all the elements on the diagonal of \(B\) are 0. \(A_2\) is a \((3 \times 3)\) matrix and \(A_0\) is a four-dimensional column vector. \(\varepsilon_t\) is a \((4 \times 1)\) column vector of errors assumed to have a zero-mean, to be uncorrelated with the exogenous variables, to be homoscedastic, and not autocorrelated. OLS estimators are biased and inconsistent because, by construction, the endogenous variables are correlated with the errors. Hence, a consistent estimation procedure like the three-stage least square (3SLS) should be used in this case. The 3SLS is both consistent and asymptotically efficient (Brooks, 2008). The instruments that we consider are the second and third lags of \(Y\) in addition to the variables listed in \(X\).

5 Empirical Findings

5.1 Results of the Break Test

The number of breaks in the unconditional variances of the four log return series is shown in Table 3. The highest number of jumps in the variance is detected in the log return of Ripple (33 breaks), while the lowest number is found in Ethereum (20

| Year | Ripple | Litecoin | Ethereum | Bitcoin |
|------|--------|----------|----------|---------|
| 2016 | 11     | 7        | 8        | 10      |
| 2017 | 8      | 8        | 5        | 6       |
| 2018 | 5      | 3        | 1        | 5       |
| 2019 | 4      | 1        | 1        | 4       |
| 2020 | 4      | 8        | 4        | 5       |
| 2021 | 1      | 0        | 1        | 0       |
| Total breaks | 33 | 27 | 20 | 30 |

Table 3 Jumps (breaks) in the unconditional variance
Table 4 Co-jumps in the unconditional variance

| Date       | Ripple | Litecoin | Ethereum | Bitcoin |
|-----------|--------|---------|----------|---------|
| 1/14/2016 | Yes    | Yes     |          | Yes     |
| 1/25/2016 | Yes    |         |          | Yes     |
| 1/11/2017 | Yes    |         |          | Yes     |
| 11/13/2018| Yes    |         |          | Yes     |
| 7/18/2019 | Yes    | Yes     |          | Yes     |
| 3/7/2020  | Yes    |         |          | Yes     |
| 3/11/2020 | Yes    | Yes     |          |         |
| 3/13/2020 | Yes    |         |          |         |
| 3/19/2020 |        | Yes     |          | Yes     |
| 6/2/2020  | Yes    |         |          | Yes     |

“Yes” implies that there is a break

breaks). Moreover, the ICSS algorithm detects 27 and 30 shifts in the variance of the log returns of Litecoin and Bitcoin respectively.

Around 70% of the jumps occurred in 2016–2018. The boom in cryptocurrency trading and the increase in the overall market size may have caused the jumps that occurred in 2016 and 2017. The market size increased from $614 K in December 2015 to $2,220 K in December 2016 and $351,228 K in December 2017. As for those in 2018, they can be explained by the fall in the cryptocurrency market. In fact, in 2018, it lost around 80% of its market capitalization. The latter decreased to $63,461 K in December 2018. Our results also show evidence of co-jumping among at least two cryptocurrencies, which is in line with the findings of Bouri et al., (2020a, b, c, d, e). Table 4 shows that most of the co-jumps occurred in the post-Covid19 era.

5.2 GARCH Estimations

Given that the return series are found to be stationary, we can estimate the GARCH models described above. The correlograms of the CORRS and PARTIALS functions of the return series are shown in Figs. 2, 3, 4, 5 in the Appendix. They are statistically significant if they lie outside the confidence interval. Therefore, we conclude that \( p \) and \( q \) are 0 in the return series of Bitcoin and Ethereum; \( p = q = 4 \) in the case of Litecoin, and \( p = q = 2 \) in the case of Ripple. The results obtained from the different GARCH models are shown in Tables 5, 6, 7, 8.

The coefficient of asymmetry (\( \gamma \)) in all the GARCH-GJR and asymmetric EGARCH models is not found to be significant. Thus, these two models were not selected for any of the four return series. This suggests that the impact of shocks on the return-volatilities is symmetric. It could imply that negative and positive shocks

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3 Dummy words. www.coinmarketcap.com

4 We consider the autocorrelation and partial autocorrelation in the return series up to one week; hence for 7 days.
Table 5 GARCH with structural breaks for the return series of Bitcoin

|                | GJR-GARCH(1,1) | ASYM-EGARCH(1,1) | GARCH(1,1) | EGARCH(1,1) | GARCH(1,0) | EGARCH(1,0) |
|----------------|----------------|------------------|------------|-------------|------------|-------------|
| \( \rho_0 \)   | 0.172(0.041)*  | 0.178(0.043)*    | 0.171(0.044)* | 0.176(0.043)* | 0.172(0.034)* | 0.176(0.035)* |
| \( \alpha_0 \)  | 1.974(1.611)   | 0.578(0.145)*    | 2.017(1.257) | 0.577(0.264)** | 1.969(1.824) | 0.580(0.247)** |
| \( \alpha_1 \)  | 0.013(0.021)   | -0.0004(0.040)   | 0.011(0.015) | 0.002(0.047) | -          | -           |
| \( \beta_1 \)   | 0.480(0.079)*  | 0.582(0.065)*    | 0.479(0.068)* | 0.574(0.072)* | 0.496(0.085)* | 0.575(0.079)* |
| \( \gamma \)    | -0.005(0.024)  | 0.015(0.037)     | -          | -           | -          | -           |
| # Of significant breaks | 27             | 29               | 28         | 28          | 23         | 28          |
| Shape           | 3.472(0.273)*  | 3.407(0.237)*    | 3.453(0.261)* | 3.413(0.232)* | 3.498(0.262)* | 3.415(0.237)* |
| JB test         | 817.88 [0.000] | 1099.265 [0.000] | [0.000]    | 1091.827 [0.000] | 806.827 [0.000] | 1090.911 [0.000] |
| LB1 test        | 2.103 [0.834]  | 2.656 [0.752]    | 2.05 [0.842] | 2.619 [0.758] | 2.156 [0.827] | 2.629 [0.756] |
| LB2 test        | 3.226 [0.665]  | 2.944 [0.708]    | 3.213 [0.667] | 3.009 [0.698] | 2.968 [0.704] | 2.985 [0.702] |
| Half-life shock (days) | 0.98           | 0.97             |            |             |            |             |

(i) *, ** and *** denote significance levels at 1%, 5% and 10% respectively. (ii) Between parentheses are robust standard deviations. (iii) Between brackets are the \( p \)-values. (iv) 30 dummies are included to account for structural breaks in the unconditional variance. The estimated coefficients for the break dummies were not shown to save place. We only report the number of dummies found significant. (v) JB is the Jarque–Bera test statistic for the normality of the errors. (vi) LB1 is the Ljung-Box test statistic for autocorrelation till order 7 in the standardized errors (null hypothesis: no autocorrelation). (vii) LB2 is the Ljung-Box test statistic for autocorrelation till order 7 in the square of the standardized errors (null hypothesis: no autocorrelation). If not rejected then standardized errors are homoskedastic. (viii) half-life is the number of days the volatility takes to return halfway back to its unconditional mean.
Table 6 GARCH with structural breaks for the return series of Ethereum

| Coefficients | GJR-GARCH(1,1) | ASYM-EGARCH(1,1) | GARCH(1,1) | EGARCH(1,1) |
|--------------|----------------|-----------------|-------------|-------------|
| $\rho_0$     | 0.081(0.086)   | 0.082(0.078)    | 0.084(0.089)| 0.086(0.066)|
| $\alpha_0$   | 10.746(4.705)**| 0.879(0.218)*   | 10.712(4.473)**| 0.874(0.205)*|
| $\alpha_1$   | 0.118(0.033)*  | 0.238(0.044)*   | 0.122(0.027)*| 0.236(0.041)*|
| $\beta_1$    | 0.578(0.063)*  | 0.714(0.061)*   | 0.578(0.059)*| 0.715(0.063)*|
| $\gamma$     | 0.009(0.046)   | −0.009(0.032)   | −          | −          |
| # of significant breaks | 17 | 19 | 18 | 20 |
| Shape        | 3.593(0.289)*  | 3.575(0.271)*   | 3.596(0.330)*| 3.578(0.288)*|
| JB test      | 576.27 [0.000] | 556.96 [0.000] | 573.473 [0.000] | 558.864 [0.000] |
| LB1 test     | 11.224 [0.047] | 11.024 [0.050] | 11.224 [0.047] | 10.986 [0.051] |
| LB2 test     | 2.215 [0.818]  | 1.639 [0.896]   | 2.215 [0.818] | 1.653 [0.894] |
| Half-life shock (days) | 1.9 | 1.9 | 1.9 | 1.9 |
| SSR          | 1675.43592     | 1669.74358      | 1676.10496 | 1670.49491 |
| LL           | −5592.09262    | −5591.75931     | −5592.0953 | −5591.79838 |
| AIC          | 11,236.18525   | 11,235.51861    | 11,234.1906| 11,233.59676|
| BIC          | 11,380.18612   | 11,379.51948    | 11,372.65298| 11,372.05914|

(i) See the note under Table 5. (ii) 20 dummies were included to account for structural breaks in the unconditional variance. (iii) SSR is the sum square of the regression, LL is the log likelihood, AIC is Akaike criteria and BIC is Schwartz criteria.

will have the same effect on the return-volatility of the four cryptocurrencies. Our comparative approach, discussed in the methodology section, leads to three conclusions. First, EGARCH(1,0) approximates well the behavior of the return series of Bitcoin. Second, EGARCH(1,1) is the model that best fits the return series of Ethereum and Litecoin. Third, GARCH(1,1) represents well the return series of Ripple. Moreover, errors from all the models are not autocorrelated till order 7 and are homoskedastic. Furthermore, the Jarque–Bera normality test shows that errors are not normally distributed. Hence, the use of a $t$-distribution for the errors rather than a normal distribution is a must. This is also confirmed by the significance of the shape parameter. Finally, the models are stable with a half-life shock ranging between one and two days. This implies that shocks are temporary and short-lived. Half of the shock is absorbed in at most 2 days.

5.3 SEM Estimation

We model the relationship between the cryptocurrencies’ return-volatilities in an SEM where the four volatilities are considered to be endogenous. These endogenous variables are also influenced by three pre-determined variables: the natural logarithm of the infectious disease equity market volatility index ($z_t$), the volatility of the S&P500...
Volatility Interdependence Between Cryptocurrencies, Equity, …

Table 7 GARCH with structural breaks for the return series of Litecoin

| Coefficients | GJR-GARCH(1,1) | ASYM-EGARCH(1,1) | GARCH(1,1) | EGARCH(1,1) |
|--------------|---------------|-----------------|------------|-------------|
| $\rho_0$     | $-0.017(0.051)$ | $-0.019(0.049)$ | $-0.026(0.043)$ | $-0.024(0.059)$ |
| $\rho_4$     | $-0.257(0.565)$ | $-0.281(0.569)$ | $-0.245(0.668)$ | $-0.281(0.013)^*$ |
| $\phi_4$     | $0.254(0.577)$ | $0.277(0.576)$ | $0.243(0.685)$ | $0.277(0.013)^*$ |
| $\alpha_0$   | $0.822(0.576)$ | $0.230(0.086)^*$ | $0.792(0.640)$ | $0.227(0.060)^*$ |
| $\alpha_1$   | $0.062(0.039)$ | $0.121(0.051)^{**}$ | $0.044(0.030)$ | $0.122(0.052)^{**}$ |
| $\beta_1$    | $0.414(0.058)^*$ | $0.580(0.051)^*$ | $0.416(0.056)^*$ | $0.580(0.026)^*$ |
| $\gamma$     | $-0.038(0.042)$ | $0.015(0.027)$ | – | – |
| # of significant breaks | 18 | 26 | 21 | 26 |
| Shape        | $3.447(0.249)^*$ | $3.325(0.213)^*$ | $3.472(0.43)^*$ | $3.328(0.214)^*$ |
| JB test      | $2310 [0.000]$ | $2668 [0.000]$ | $2310 [0.000]$ | $2678 [0.000]$ |
| LB1 test     | $4.244 [0.514]$ | $2.299 [0.806]$ | $4.244 [0.514]$ | $2.294 [0.807]$ |
| LB2 test     | $2.561 [0.767]$ | $4.862 [0.432]$ | $2.561 [0.767]$ | $4.814 [0.438]$ |
| Half-life shock (days) | 0.93 | 0.89 | – | – |

(i) See the note under Table 5. (ii) 27 dummies were included to account for structural breaks in the unconditional variance. (iii) AR(1 to 3) and MA(1 to 3) in the mean equation were not found significant.

(VIX), and the volatility of the bond market (VXTLT). We know that volatility captures market sentiment, in particular the degree of fear among market participants. Hence, it measures the degree and the magnitude of the variations in the price when it deviates from its equilibrium level. The more dramatic and frequent the swings in the price are, the higher the level of volatility will be, and vice versa. Hence, we interpret an increase in volatility as a deviation from the market equilibrium and a decrease in volatility as a convergence to market equilibrium.

We check first the validity of the instruments and the correlation in the residuals. The $J$-test statistic is 1.249 with a $p$-value of 0.869. Hence, there is enough evidence in favor of the exogeneity of the instruments. The Ljung-Box test does not reject the null of no-autocorrelation in the residuals at orders one and two. Moreover, the correlation between the residuals and the exogenous variables is zero. The Breush-Pagan test statistic is 7727.58 and its $p$-value is 0. Thus, the null hypothesis of no correlation in the residuals across the four equations was rejected.

Our results shown in Table 9 suggest that VIX does not affect the return-volatilities of the four cryptocurrencies ($\sigma_{lit}^t$, $\sigma_{et}^t$, $\sigma_{bit}^t$, $\sigma_{rip}^t$). However, an increase in VXTLT increases the volatility of Litecoin and Bitcoin ($\sigma_{lit}^t$ and $\sigma_{bit}^t$) but decreases the volatility of Ethereum ($\sigma_{et}^t$). On the other hand, a 1% increase in the infectious disease equity market volatility ($z_t$) negatively affects the volatility of Litecoin ($\sigma_{lit}^t$) and Bitcoin ($\sigma_{bit}^t$) but positively affects the volatility of Ethereum ($\sigma_{et}^t$). Furthermore, our results show evidence for a positive instantaneous and bidirectional volatility spillover effect between two pairs: Ethereum-Litecoin ($\sigma_{et}^t$ and $\sigma_{lit}^t$) and Ethereum-Bitcoin ($\sigma_{et}^t$ and
Table 8 GARCH with structural breaks for the return series of Ripple

|                | GJR-GARCH(1,1) | ASYM-EGARCH(1,1) | GARCH(1,1) | EGARCH(1,1) |
|----------------|----------------|------------------|------------|-------------|
| $\rho_0$       | −0.130(0.047)* | −0.152(0.036)*   | −0.133(0.042)* | −0.115(0.076) |
| $\rho_1$       | 0.865(0.144)*  | 0.281(0.031)*    | 0.862(0.141)* | 0.775(0.446)** |
| $\phi_1$       | −0.947(0.128)* | −0.384*(0.009)*  | −0.944(0.129)* | −0.870(0.402)** |
| $\rho_2$       | −0.484(0.272)**| −0.012(0.081)    | −0.487(0.264)**| −0.320(0.757)  |
| $\phi_2$       | 0.506(0.254)** | 0.012(0.072)     | 0.507(0.249)  | 0.349(0.716)   |
| $\alpha_0$     | 4.045(2.497)   | 0.666(0.226)*    | 4.164(2.306)** | 0.684(0.225)*  |
| $\alpha_1$     | 0.197(0.079)** | 0.375(0.061)*    | 0.197(0.052)* | 0.379(0.066)*  |
| $\beta_1$      | 0.347(0.062)*  | 0.526(0.050)*    | 0.324(0.050)* | 0.529(0.048)*  |
| $\gamma$       | −0.023(0.080)  | 0.014(0.049)     | –           | –            |
| # of signifi- | 30             | 29               | 28          | 28           |
| cant breaks    |                |                  |             |              |
| Shape          | 3.009(0.208)*  | 3.033(0.180)*    | 2.950(0.192)* | 3.032(0.198)* |
| JB test        | 1197.271 [0.000] | 970.163 [0.000] | 1159.806 [0.000] | 980.249 [0.000] |
| LB1 test       | 12.257 [0.031] | 14.357 [0.013] | 12.191 [0.032] | 13.931 [0.016] |
| LB2 test       | 2.861 [0.721]  | 2.725 [0.742]   | 2.533 [0.771] | 2.711 [0.744]  |
| Half-life shock| 1.13           | –                | 1.06         | –            |
| shock (days)   |                |                  |             |              |

(i) See the note under Table 5. (ii) 33 dummies were included to account for structural breaks in the unconditional variance

$\sigma_{t}^{bit}$ on one side and a negative instantaneous and bidirectional volatility spillover effect between Bitcoin and Litecoin ($\sigma_{t}^{bit}$ and $\sigma_{t}^{lit}$) on the other side. Interestingly, the magnitude of the bidirectional spillover is higher for large cryptocurrencies. We also identify a unidirectional instantaneous volatility spillover running from $\sigma_{t}^{rip}$ to the three other cryptocurrencies. The impact is positive on the volatility of Bitcoin and Litecoin ($\sigma_{t}^{bit}$ and $\sigma_{t}^{lit}$) but negative on the volatility of Ethereum ($\sigma_{t}^{et}$). Finally, our results suggest a short-lived spillover effect. The lagged effects of $\sigma_{t-1}^{lit}$, $\sigma_{t-1}^{et}$, $\sigma_{t-1}^{bit}$ and $\sigma_{t-1}^{rip}$ on $\sigma_{t}^{lit}$, $\sigma_{t}^{et}$ and $\sigma_{t}^{bit}$ compensate the instantaneous effects rendering any deviation from equilibrium transitory and shocks short-lived.

5.4 Discussion of Results

We show evidence for bidirectional or unidirectional volatility spillovers among the four cryptocurrencies. On one hand, a positive instantaneous and bidirectional volatility spillover effect exists between Ethereum-Litecoin and Ethereum-Bitcoin. On the other hand, a negative instantaneous and bidirectional volatility spillover effect exists between Bitcoin-Litecoin. These results support $H_1$ which states that bi-directional volatility spillovers exist between some of the selected cryptocurrencies. We also identify a unidirectional instantaneous volatility spillover running from Ripple to the three other cryptocurrencies. The impact is positive on the volatility of Bitcoin and Litecoin.
Table 9 SEM results

|                  | $\sigma^\text{lit}_t$ | $\sigma^\text{et}_t$ | $\sigma^\text{bit}_t$ | $\sigma^\text{rip}_t$ |
|------------------|------------------------|------------------------|------------------------|------------------------|
| constant         | $-27.522$ [0.995]      | $14.764^{**}$ [0.041]  | $-2.762^{***}$ [0.097] | $19.530$ [0.995]       |
| $\sigma^\text{lit}_t$ | $-0.536^{*}$ [0.000]  | $-0.100^{*}$ [0.004]  | $0.711$ [0.902]        |                        |
| $\sigma^\text{et}_t$ | $1.858^{*}$ [0.000]   | $-0.100^{*}$ [0.004]  | $0.711$ [0.902]        |                        |
| $\sigma^\text{bit}_t$ | $-9.608^{*}$ [0.002]  | $5.206^{*}$ [0.000]   | $6.954$ [0.893]        |                        |
| $\sigma^\text{rip}_t$ | $1.397^{*}$ [0.000]   | $-0.753^{*}$ [0.000]  | $1.42^{*}$ [0.000]    | $0.760$ [0.573]        |
| $\sigma^\text{llit}_{t-1}$ | $-1.063^{*}$ [0.000]  | $0.572^{*}$ [0.000]   | $-0.108^{*}$ [0.000]  | $0.760$ [0.573]        |
| $\sigma^\text{et}_{t-1}$ | $0.422^{*}$ [0.000]   | $-0.227^{*}$ [0.000]  | $0.042^{*}$ [0.001]   | $-0.302$ [0.949]       |
| $\sigma^\text{bit}_{t-1}$ | $-1.601^{*}$ [0.000]  | $0.861^{*}$ [0.000]   | $-0.162^{*}$ [0.000]  | $1.143$ [0.844]        |
| $\sigma^\text{rip}_{t-1}$ | $8.716^{*}$ [0.001]   | $-4.719^{*}$ [0.000]  | $0.904^{*}$ [0.000]   | $-6.301$ [0.877]       |
| $z_t$            | $-16.479^{***}$ [0.054]| $8.880^{**}$ [0.047]  | $-1.682^{***}$ [0.060]| $11.799$ [0.973]       |
| $\text{VIX}$     | $1.319$ [0.199]        | $-0.709$ [0.185]       | $0.133$ [0.220]        | $-0.939$ [0.985]       |
| $\text{VXTLT}$   | $2.893^{***}$ [0.083]  | $-1.559^{***}$ [0.083]| $0.294^{***}$ [0.099]  | $-2.072$ [0.993]       |
| AR(1)            | $0.108$ [0.741]        | $0.093$ [0.759]        | $0.601$ [0.803]        | $0.079$ [0.778]        |
| AR(2)            | $0.323$ [0.850]        | $0.304$ [0.858]        | $0.261$ [0.877]        | $0.287$ [0.866]        |

(i) *, ** and *** denote significance levels at 1%, 5% and 10% respectively. (ii) Between brackets are the $p$-values. (iii) AR(1) and AR(2) are the Ljung-Box statistics for autocorrelation in the errors at orders one and two respectively.

but negative on the volatility of Ethereum. These results show that cryptocurrencies smaller than Bitcoin become important players in the cryptocurrency market dethroning Bitcoin as a crypto market-dominant as claimed by Anto nakakis et al. (2019), Ji et al. (2019), Koutmos (2018), and Kumar & Ajaz (2019). Our results are in line with Bouri et al. (2020a, 2020b, 2020c, 2020d, 2020e), Corbet et al. (2018), Katsiampa et al. (2019b), Shahzad et al. (2021), Shi et al. (2020), and Zięba et al. (2019).

These studies identify co-movement patterns between pairs of cryptocurrencies that may be similar or different from those we identify in this study. They all underline the importance of smaller cryptocurrencies to the network of return and/or volatility shocks. This is due to the peculiarity of the cryptocurrency supply mechanism. In the same context, Qureshi et al. (2020) show that cryptocurrencies less prominent than Bitcoin such as Ethereum and Ripple are the main source of contagion in the cryptocurrency market. In line with Qureshi et al. (2020), our results show that Ripple is not affected by shocks stemming from other cryptocurrencies but transmits shocks to Bitcoin, Ethereum, and Litecoin, which identifies it as a major transmitter.

Finally, our results suggest a short-lived spillover effect. The lagged effects of the volatility of Litecoin, Ethereum, Bitcoin, and Ripple on the volatility of Litecoin, Ethereum, Bitcoin, and Ripple ($\sigma^\text{llit}_t$, $\sigma^\text{et}_t$ and $\sigma^\text{bit}_t$) compensate the instantaneous effects rendering any deviation from equilibrium transitory and shocks short-lived. Hence, we could imply that the cryptocurrency market is efficient: it absorbs the impact of exogenous shocks and autocorrects deviations. This result goes in line with the GARCH findings and the conclusion that shocks in the cryptocurrency market are transitory.
with a half-life shock not exceeding two days. Our finding contradicts the results of Bouri et al. (2019) and Abakah et al. (2020) who find shocks to major cryptocurrencies to be persistent causing prices to divert from their long-run means. Abakah et al. (2020) show that accounting for structural breaks reduces the degree of persistence in the cryptocurrency market.

Additionally, we show in Table 9 that $VIX$ does not affect the return-volatilities of the four major cryptocurrencies considered in our study. This could imply that cryptocurrencies are detached from the global equity market and are endowed with safe heaven or hedging properties against traditional assets. These results do not support $H_{2a}$, but corroborate with those of Corbet et al. (2018), Aslanidis et al. (2019), Tiwari et al. (2019), Mariana et al. (2020), and Bouri et al., (2020a, 2020b, 2020c, 2020d, 2020e) who show that most cryptocurrencies play the role of either safe haven or hedge for US equity indices. The results are also in line with Anyfantaki et al. (2021) who show that the inclusion of cryptocurrencies in traditional portfolios is found to be a good diversification option for risk-averse investors. There is no straightforward theory that explains the hedging and safe haven properties of cryptocurrencies against traditional assets. An explanation could be because of their detachment from the global financial system and the singularity of the factors that determine their value such as innovative technological features, attractiveness and media attention. However, the wide acceptance of cryptocurrencies among institutional investors and the maturity of the market recently contributed to increasing the correlation between stock markets and cryptocurrencies, altering their hedging and safe haven properties in specific periods.

Our results show that the $VXTLT$ representing the bond market volatility affects the volatility of Litecoin, Bitcoin, and Ethereum. This implies that the bond market is not detached from the market of the aforementioned cryptocurrencies. These results support $H_{2b}$. An increase in $VXTLT$ increases the volatilities of Litecoin and Bitcoin but decreases the volatility of Ethereum. Hence, this could indicate that deviations in the bond market cause Litecoin and Bitcoin to deviate from equilibrium while Ethereum converges to equilibrium. Interestingly, the two biggest cryptocurrencies in terms of market capitalization react in opposite directions to $VXTLT$. These results can guide portfolio managers and individual investors to make investment decisions based on their risk appetite. In periods of high volatility in the bond market, risk-averse investors are recommended to switch to Ethereum rather than Bitcoin and Litecoin as the latter cryptocurrencies move with the market. This contributes to the scarce literature that examined the connectedness of cryptocurrencies with bond markets (Anyfantaki et al., 2021; Ciner & Lucey, 2022; Karim et al. 2022). Our results call for a closer look into the difference in processing Bitcoin and Ethereum. While both operate on blockchain technology, Ethereum seems to be a far more robust ledger technology used by companies to build new programs given its potential to impact projects and processes across all industries. Hence, as Ethereum has opened the door for a wide variety of unique innovations, investors may consider it differently when selecting a portfolio of assets.

Furthermore, our findings show that a 1% increase in the infectious disease equity market volatility ($z_t$) negatively affects the volatility of Litecoin ($\sigma_{\text{lit}}^t$) and Bitcoin ($\sigma_{\text{bit}}^t$) but positively affects the volatility of Ethereum ($\sigma_{\text{et}}^t$). Hence, Litecoin, Bitcoin, and Ethereum are impacted by the US equity market when the volatility on the latter
is caused by pandemic outbreaks and the adopted response policies. Hence, we find sufficient evidence to support \( H_3 \). Financial uncertainty in the US market induced by pandemic outbreaks pushes the price of Litecoin and Bitcoin to converge back to equilibrium and the price of Ethereum to diverge from its equilibrium. However, the magnitude is greater on the volatility of Litecoin (−0.164) compared to that of Bitcoin (−0.016). This is consistent with recent studies by Fasanya et al. (2021) and Polat and Kabakçı Günay (2021) who find that volatility spillovers experience significant changes during major market crises. It is worth noting that spillover effect patterns may effectively differ as suggested by Shahzad et al. (2021). They show that the interconnectedness measures among cryptocurrencies are time-variant, particularly when they consider switching volatility regimes during the Covid-19 outbreak.

### 5.5 Robustness Check Analysis

To check the robustness of our findings, we estimate two additional models with different specifications.

In the first one, we replace the VIX index with the Chicago Board Options Exchange DJIA volatility (VXD) index. The VXD index estimates the expected volatility of the Dow over the next 30 days and is a good alternative for the VIX. This is confirmed by the very high historical correlation between the two indices. Results in Table 10 are similar to those previously found in Table 9. First, the volatility of the US equity market, measured by the VXD, does not affect the volatility of the four cryptocurrencies. Second, the volatility of the Ripple was not affected by the volatility of Bitcoin, Litecoin, and Ethereum. Third, the coefficients have the same magnitudes and signs as those found in Table 9.

In the second robustness check exercise, we extend our initial model by including the Merrill Lynch Option Volatility Estimate (MOVE) index. The MOVE index measures the implied volatility of mainly short- and medium-term US bonds. Hence, it captures uncertainty in short- to medium-term US bonds. By considering the MOVE and the VXTLT indices in one model, we take into consideration the volatilities of long-term US bonds and the short/medium-term US bonds. Results in Table 11 support all our previous findings. Moreover, MOVE is found significant and negative in the case of Litecoin and Bitcoin, and positive in the case of Ethereum. Hence, any increase in uncertainties in short- to medium-term US bonds increases the volatility of Ethereum but decreases the volatility of Litecoin and Bitcoin. This result complements well the previous one obtained when using the VXTLT index alone. The latter measures the long-term US bond market volatility and our results show that investors with long-term investment horizons should favor Ethereum. However, investors with short- to medium-term investment horizons are recommended to consider Bitcoin and Litecoin.

### 6 Conclusion and Policy Recommendations

This study investigates volatility spillovers among four major cryptocurrencies (Bitcoin, Ethereum, Ripple, and Litecoin) and their interconnections with the US stock
and bond markets. When modelling the volatilities in the GARCH framework, we take into consideration the presence of structural breaks. We adopt a comparative approach to select the GARCH model that best fits our data and we use the Iterated Cumulative Sums of Squares (ICSS) algorithm proposed by Inclán and Tiao (1994) to test for structural breaks in the unconditional variance. Failing to account for break points may lower the power of the modelling approach and lead to invalid conclusions and inferences, especially with evidence of booms and busts in the cryptocurrency market (Cheah & Fry, 2015). To the best of our knowledge, none of the previous studies accounted for structural breaks during the Covid-19 period. We also estimate a Simultaneous Equation Model (SEM) to investigate the spillover effect between and within cryptocurrency volatilities. We include three exogenous variables in the SEM: (i) the US stock market volatility measured by the VIX index; (ii) the US bond market volatility measured by the VXTLT index; and (iii) the uncertainties in the financial market caused by epidemics and diseases outbreak as proxied by the daily Infectious Disease Equity Market Volatility Tracker (EMVID).

Our study contributes to the academic debate in four ways. First, it sheds light on the dynamics of volatility spillovers among Bitcoin, Ethereum, Ripple, and Litecoin around the Covid-19 outbreak. Second, it looks at the interconnection between the

### Table 10 SEM results with VXD index as a substitute to VIX index

|          | \(\sigma_{i,t}^{lit}\) | \(\sigma_{i,t}^{et}\) | \(\sigma_{i,t}^{bit}\) | \(\sigma_{i,t}^{rip}\) |
|----------|-------------------------|-----------------------|------------------------|------------------------|
| constant | -29.907 [0.994]         | 16.363*** [0.023]     | -3.043*** [0.081]      | 21.346 [0.994]         |
| \(\sigma_{i,t}^{lit}\) | -                      | 0.547* [0.000]        | -0.101* [0.005]        | 0.715 [0.918]          |
| \(\sigma_{i,t}^{et}\) | 1.821* [0.000]         | -                     | 0.187* [0.000]         | -1.308 [0.870]         |
| \(\sigma_{i,t}^{bit}\) | -9.443* [0.003]        | 5.221* [0.000]        | -                      | 6.883 [0.904]          |
| \(\sigma_{i,t}^{rip}\) | 1.389* [0.000]         | -0.763* [0.000]       | 0.144* [0.000]         | -                      |
| \(\sigma_{i,t-1}^{lit}\) | -1.056* [0.000]        | 0.580* [0.000]        | -0.109* [0.000]        | 0.760 [0.589]          |
| \(\sigma_{i,t-1}^{et}\) | 0.426* [0.000]         | -0.234* [0.000]       | 0.044* [0.002]         | -0.306 [0.954]         |
| \(\sigma_{i,t-1}^{bit}\) | -1.564* [0.000]        | 0.858* [0.000]        | -0.160* [0.000]        | 1.123 [0.867]          |
| \(\sigma_{i,t-1}^{rip}\) | 8.577* [0.001]         | -4.739* [0.000]       | 0.905* [0.000]         | -6.244 [0.895]         |
| \(z_t\) | -17.163*** [0.053]      | 9.440** [0.043]       | -1.783*** [0.052]      | 12.381 [0.968]         |
| VXD     | 1.364 [0.195]           | -0.749 [0.176]        | 0.141 [0.199]          | -0.981 [0.965]         |
| VXTLT   | 3.040*** [0.051]        | -1.669*** [0.054]     | 0.313*** [0.081]       | -2.186 [0.991]         |
| AR(1)   | 0.222 [0.637]           | 0.198 [0.655]         | 0.143 [0.704]          | 0.174 [0.6758]         |
| AR(2)   | 0.424 [0.808]           | 0.397 [0.819]         | 0.330 [0.847]          | 0.371 [0.830]          |

(i) *, ** and *** denote significance levels at 1%, 5% and 10% respectively. (ii) Between brackets are the \(p\)-values. (iii) AR(1) and AR(2) are the Ljung-Box statistics for autocorrelation in the errors at orders one and two respectively. We do not reject the null that errors are not autocorrelated. (iv) The \(J\)-test statistic is 1.280 with a \(p\)-value of 0.864. Hence, we do not reject the null that the instruments are exogenous. (v) The correlation between the residuals and the exogenous variables is zero. (vi) The Breush-Pagan test statistic is 7727.48 and its \(p\)-value is 0. Thus, the null hypothesis of no correlation in the residuals across the four equations was rejected.
Table 11 SEM results with MOVE index

|       | $\sigma_{lit}^t$ | $\sigma_{ett}^t$ | $\sigma_{bit}^t$ | $\sigma_{rip}^t$ |
|-------|-----------------|-----------------|-----------------|-----------------|
| constant | 17.810 [0.999] | $-9.192 [0.468]$ | $1.565 [0.473]$ | $-12.268 [0.999]$ |
| $\sigma_{lit}^t$ | $-9.192 [0.468]$ | $-0.087 [0.000]$ | $0.687 [0.965]$ |
| $\sigma_{ett}^t$ | $1.936 [0.000]$ | $-0.169 [0.000]$ | $-1.337 [0.968]$ |
| $\sigma_{bit}^t$ | $-11.295 [0.003]$ | $5.852 [0.000]$ | $-7.846 [0.985]$ |
| $\sigma_{rip}^t$ | $1.442 [0.000]$ | $-0.745 [0.000]$ | $0.126 [0.000]$ | $-1$ |
| $\sigma_{rip}^{t-1}$ | $-1.102 [0.001]$ | $0.570 [0.000]$ | $-0.096 [0.000]$ | $0.764 [0.870]$ |
| $\sigma_{lit}^{t-1}$ | $0.445 [0.000]$ | $-0.229 [0.000]$ | $0.039 [0.002]$ | $-0.307 [0.986]$ |
| $\sigma_{ett}^{t-1}$ | $-1.646 [0.000]$ | $0.850 [0.000]$ | $-0.144 [0.000]$ | $1.137 [0.959]$ |
| $\sigma_{bit}^{t-1}$ | $10.120 [0.001]$ | $-5.241 [0.000]$ | $0.895 [0.000]$ | $-7.025 [0.983]$ |
| $z_t$ | $-33.226 [0.003]$ | $17.148 [0.003]$ | $-2.909 [0.007]$ | $22.930 [0.996]$ |
| $VIX$ | $1.279 [0.235]$ | $-0.660 [0.218]$ | $0.111 [0.243]$ | $-0.885 [0.991]$ |
| $VXTLT$ | $7.285 [0.004]$ | $-3.757 [0.006]$ | $0.637 [0.012]$ | $-5.020 [0.995]$ |
| MOVE | $-1.236 [0.024]$ | $0.637 [0.026]$ | $-0.108 [0.043]$ | $0.851 [0.998]$ |
| AR(1) | $0.072 [0.788]$ | $0.078 [0.779]$ | $0.096 [0.755]$ | $0.080 [0.776]$ |
| AR(2) | $0.296 [0.862]$ | $0.299 [0.860]$ | $0.312 [0.855]$ | $0.298 [0.861]$ |

(i) See note under Table 10. (ii) The J-test statistic is 1.346 with a $p$-value of 0.853. Hence, we do not reject the null that the instruments are exogenous. (iii) The correlation between the residuals and the exogenous variables is zero. (iv) The Breush-Pagan test statistic is 7727.89 and its $p$-value is 0. Thus, the null hypothesis of no correlation in the residuals across the four equations was rejected.

The empirical findings are three-fold. First, we identify: (i) a positive instantaneous and bidirectional volatility spillover effect between Ethereum and Litecoin and between Ethereum and Bitcoin, and (ii) a negative instantaneous and bidirectional volatility spillover effect between Bitcoin and Litecoin. Interestingly, the magnitude of the spillover effect is larger for major cryptocurrencies. Ripple seems to be disconnected from the other cryptocurrencies. However, it transmits positive shocks to Bitcoin and Litecoin and negative ones to Ethereum. Overall, the identified volatility spillover effects are short-lived and transitory with a half-life shock of fewer than two days. Second, we show that the US stock market is detached from the studied cryptocurrency market offering hedging and safe haven opportunities to investors. However, disturbances in the bond market cause Bitcoin and Litecoin to deviate from equilibrium and Ethereum to converge to equilibrium. We notice that the two biggest cryptocurrencies in terms of market capitalization (Bitcoin and Ethereum) react in opposite directions to the volatility in the US bond market. This calls for a closer...
look into the difference in processing Bitcoin and Ethereum and how this distinction can be regarded by investors. Our results are important for investors willing to build an optimal portfolio by diversifying their holdings across major cryptocurrencies and conventional assets, especially during extreme events. Third, we show that high economic and financial uncertainties in the US stock market due to pandemic outbreaks affect the volatility of Bitcoin, Litecoin, and Ethereum. Precisely, it pushes the price of Litecoin and Bitcoin to converge to equilibrium while it causes Ethereum to shift away from its equilibrium. To check the robustness of our findings, we estimate two additional models with different specifications. The results of both robustness checks support our main findings.

Our empirical findings show the important role of cryptocurrencies in investment portfolios given their relative detachment from the majority of mainstream assets. Our results also highlight the importance of accounting for structural breaks in cryptocurrency data to infer more accurate conclusions and recommendations to investors in terms of optimal hedging opportunities and portfolio diversification strategies, in normal and turbulent periods. However, diversification is not only about correlation. More specifically, some of our findings suggest that Ripple exhibits a new feature when compared to the remaining three cryptocurrencies, which brings a positive impact on its return. As such, investors could prefer to hold it in their portfolios. In addition, investors who seek protection from downward movements in bond markets could benefit from taking a position in Ethereum, especially in times of extreme uncertainty such as the Covid-19 outbreak. Our results have practical implications for investors and contribute to the contemporary debate about the speculative nature of cryptocurrencies. As cryptocurrencies gained maturity and wider acceptance among investors, this increased their integration with stocks and bonds. Investors and fund managers should then be aware of this integration when including crypto-assets with other asset classes in the same portfolio. The findings also have implications for policymakers as they help them time their intervention to stabilize markets and control uncertainties inherent to stressful periods. Policymakers can rely on our results in terms of the magnitude of spillovers to take the necessary measures to influence the sentiment of investors and businesses and reduce their risk.

We recognize two potential limitations. First, we can use intraday data instead of daily data. However, the former are available for free in Reuters or Bloomberg for a period of fewer than six months. Data provider offers them for a longer period but at a high cost. The second limitation is attributed to the restricted sample size due to the late birth of some cryptocurrencies.

Further research may observe the behavior of cryptocurrencies with respect to the increase in investors’ awareness of sustainability and energy consumption. This would change the investors’ preferences. Future studies could also investigate volatility spillovers and connectedness among various classes of cryptocurrencies such as coins, tokens, and stablecoins and use artificial intelligence methods such as wavelet analysis based on intraday data.

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Volatility Interdependence Between Cryptocurrencies, Equity, …

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**Appendix**

See Figs. 1, 2, 3, 4, 5 and Table 12.

**Fig. 1** Log returns series

**Fig. 2** Correlogram of the return series of Bitcoin. *Note:* Horizontal lines are the 95% confidence interval for the autocorrelations.
Fig. 3 Correlogram of the return series of Ethereum. *Note:* Horizontal lines are the 95% confidence interval for the autocorrelations.

Fig. 4 Correlogram of the return series of Litecoin. *Note:* Horizontal lines are the 95% confidence interval for the autocorrelations.

Fig. 5 Correlogram of the return series of Ripple. *Note:* Horizontal lines are the 95% confidence interval for the autocorrelations.
Table 12 Sources and definition of the variables

| Variable | Definition | Source |
|----------|------------|--------|
| VIX      | Chicago Board Options Exchange (CBOE) volatility index (VIX) measures the market risk and investors’ sentiments about the future volatility of the S&P500 index | Bloomberg |
| VXTLT    | Chicago Board Options Exchange (CBOE) 20+ Year Treasury Bond ETF Volatility Index | Bloomberg |
| $z_t$    | The daily Infectious Disease Equity Market Volatility Tracker (EMVID) is a newspaper-based index that captures stock market volatility in the USA attributed to infectious disease outbreaks or policy responses to such outbreaks. The index is re-scaled as follows: $z_t = \ln(e + EMVID_t)$ | Economic Policy Uncertainty: https://www.policyuncertainty.com/infectious_EMV.html |
| $R_t$    | Daily continuous returns for Ripple, Litecoin, Ethereum, and Bitcoin. It is calculated as follows: $R_t = 100 * \log\left(\frac{P_t}{P_{t-1}}\right)$ where $P_t$ is the closing price in $t$ and $P_{t-1}$ is the lagged closing price | Price series are collected from www.coinmarketcap.com |

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