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Quantifying Return and Volatility Spillovers among Major Cryptocurrencies: A VAR-BEKK-GARCH Analysis

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Önde Gelen Kriptopara Birimleri Arasında Getiri ve Oynaklık Yayılımlarının Ölçülmesi: VAR-BEKK-GARCH Analizi

Öz

Bu çalışma sekiz ana kripto para birimlerinden Bitcoin, Ethereum, Litecoin, Ripple, Stellar, Bitcoin Cash, Cardano ve EOS arasındaki yayılma etkilerini VAR-BEKK-GARCH modeli ile araştırmaktadır. Çalışmanın sonuçları, kripto para birimleri arasında çift ve tek yönlü yayılma etkilerinin olduğuna işaret etmektedir. Ayrıca, sonuçlar bazı kripto para birimlerinin verici görevi görürken, bazılarının ise alıcı görevi gördüğünü ve analiz edilen kripto para birimleri arasında Litecoin'in en yüksek verici, Stellar'ın ise alıcı görevi gören tek kripto para birimi olduğunu göstermektedir. Kripto para birimlerinin birbirleriyle entegre olmaları aralarındaki bağımlılığı desteklemektedir ve bu sonuçlar yatırımcılar için yatırım stratejileri ve düzenleyiciler için politika çıkarımları sağlamalarına neden olmaktadır.

Anahtar Kelimeler: Kriptoparalar, Getiri Yayılımı, Oynaklık Yayılımı, Yatırım Stratejisi, VAR-BEKK-GARCH

JEL Kodları: C5, C32, G1

Quantifying Return and Volatility Spillovers among Major Cryptocurrencies: A VAR-BEKK-GARCH Analysis

Abstract

This study investigates mean and volatility spillover effects among eight major cryptocurrencies; Bitcoin, Ethereum, Litecoin, Ripple, Stellar, Bitcoin Cash, Cardano and EOS utilizing VAR-BEKK-GARCH model. The results point out that there are bidirectional and unidirectional spillover effects among these major cryptocurrencies. Moreover, the findings indicate that some cryptocurrencies are the transmitter, while others act as a receiver and among all, Litecoin is the highest transmitter, and Stellar is the only one that acts as a receiver. The interdependence among cryptocurrencies supports that they are becoming more integrated and thereby, provides important investment strategies for investors and policy implications for regulators.

Keywords: Cryptocurrencies, Return Spillovers, Volatility Spillovers, Investment Strategy, VAR-BEKK-GARCH

JEL Codes: C5, C32, G1

Araştırma ve Yayın Etiği Beyanı	Bu çalışma bilimsel araştırma ve yayın etiği kurallarına uygun olarak hazırlanmıştır.
Yazarların Makaleye Olan Katkıları	Yazarların makaleye katkısı eşit orandadır.
Çıkar Beyanı	Yazarlar açısından ya da üçüncü taraflar açısından çalışmadan kaynaklı çıkar çatışması bulunmamaktadır.

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1. Introduction

With the rapid evolution of blockchain technology, cryptocurrencies have attracted the attention of many market practitioners, policymakers, and regulators. As a new digital currency, cryptocurrency allows people to make transactions directly with each other through an online system without getting permission from any financial institution or regulator (Nakamoto, 2008).

Bitcoin was the first cryptocurrency, introduced as open-source software by Satoshi Nakamoto in 2009. It may not be surprising that Bitcoin, which is completely decentralized and not subject to government regulations or restrictions, captured the interest of the public following the 2007-2008 global financial and economic crisis and the subsequent loss of confidence in financial integrity. As of February 2022, the market capitalization of Bitcoin surpassed $833 billion, and the market capitalization of cryptocurrencies reached a value of $1,713 billion[1]. The number of cryptocurrencies increases daily, and the total number reached 9,359 in February 2022. Although most are developed on the basis of blockchain technology, each of them may have different characteristics to attract investors. Their specific characteristics will have impacts on their prices as well as their volatilities. Most studies in the empirical literature have paid attention to Bitcoin only, and the return and volatility spillovers among different cryptocurrencies have been given much less importance. This motivation encourages us to focus on not only Bitcoin but also other cryptocurrencies, in addition to other developments, such as increasing trade volumes of different cryptocurrencies compared to Bitcoin, and their attractively detached price behaviors with respect to economic fundamentals (Briere et al., 2015), and higher volatility patterns they exhibit to attract speculators, investors and academicians. Furthermore, higher interdependency among cryptocurrencies along with the comparably higher market volatility inhibits investors to minimize their risks, thereby, dampening the market dynamics (Frances et al., 2018). Specifically, investors, risk managers, and arbitrageurs need an understanding of the existence as well as the direction of the shock and volatility transmission effects among different cryptocurrencies while trading (Koutmos, 2018), and thus, enabling them to choose the most appropriate ones for such a diversification with respect to their risk preferences (Yi et al., 2018). Therefore, our aim is to explore the spillover effects among eight major cryptocurrencies: Bitcoin (BTC), Ethereum (ETH), Litecoin (LTC), Ripple (XRP), Stellar (XLM), Bitcoin Cash (BCH), Cardano (ADA) and EOS. Additionally, this study employs VAR-BEKK-GARCH model for the empirical analysis of these selected currencies in the crypto market.

This parametric model introduced by Engle and Kroner (1995) with positive precision constraints represents an effective method for modeling volatility. It provides a positive definite variance-covariance matrix, which is efficient in reducing the number of estimated parameters, and thus allows a more precise description and measurement of the volatility spillover effects among all the variables. According to Ross (1989), the volatility of asset price is directly connected with information transmission, which indicates the spillover effect. Hence, the remarkable feature for market participants is to realize the volatility spillovers among cryptocurrencies according to their interdependence and interconnectedness. Considering the importance of diversification benefits, the aim of this study is to understand the return, shock

[1] The information is gathered from https://coinmarketcap.com/tr/.

and volatility transmission effects among the major cryptocurrencies traded in the crypto market. Research, therefore, has questioned if there exist any return and volatility spillovers between major cryptocurrencies by using a well-developed multivariate GARCH model with BEKK specification over a specific period.

Our study has the following contributions to the existing empirical literature: First of all, we consider more selection of cryptocurrencies, using not only the major cryptocurrencies such as Bitcoin and Ethereum, but also Litecoin, Ripple, Stellar, Bitcoin Cash, Cardano and EOS, which, despite being less popular than Bitcoin and Ethereum, are still preferred by many investors. Secondly, using the more comprehensive and up-to-date dataset, the investigation of the volatility spillover effects among cryptocurrencies from June 1, 2018, to September 7, 2021 provides an overview of the information transmission mechanism between cryptocurrencies and stipulates valuable information for all market participants. The existence of a higher level of volatility spillovers among crypto assets can reduce portfolio diversification benefits and the findings are also crucial for constructing accurate financial asset pricing models and predicting future volatility in cryptocurrencies. The absence or existence of the spillover effects, as well as the direction, helps market participants to improve risk management strategies. The awareness of the information transmission mechanism in cryptocurrencies can be used by investors as well as other market practitioners and regulators to modify the assets in the portfolios and/or generate investment or hedging strategies to eliminate the risks. Finally, the methodology employed for the empirical analysis is a bivariate MGARCH with the BEKK parameterization, which is vital for future studies of analyzing and predicting spillover effects. Unlike most of the studies which are concentrated on only main cryptocurrencies such as Bitcoin, Ethereum, Litecoin using MGARCH model for only the volatility interdependency, it is vital to note that we, additionally, use it to explore the return spillover effects between large pairs of cryptocurrencies. The use of this model is advantageous since it allows us to better understand the return and volatility transmission for the major cryptocurrency pairs.

The structure of this study is as follows. Section 2 is related to the literature review that highlights some important studies in cryptocurrencies and volatility spillover effects. Section 3 describes the dataset used, provides some data sources, and also discusses the summary statistics of the eight cryptocurrencies selected. Section 4 elaborates the methodology adopted and Section 5 presents the results of the analysis. Finally, Section 6 discusses the results with the empirical literature and concludes with some policy implications and suggests some potential avenues for further empirical research.

2. Literature Review

The rapid emergence of cryptocurrencies has caused many researchers around the globe to debate whether cryptocurrencies, especially Bitcoin, constitute a new financial asset class. With Bitcoin having significant attention among all of the cryptocurrencies, studies investigating the relationship between Bitcoin and financial assets have become common in the literature. The findings of these studies generally suggest that Bitcoin acts as a hedge (Dyhrberg, 2016; Bouri et al., 2017a; Urquhart and Zhang, 2019) and a safe haven (Smales, 2019; Shahzad et al., 2019; Conlon et al., 2020) against financial assets. When analyzing the cryptocurrencies in isolation, Bitcoin tends to have the lowest market risk even during Covid-19 pandemic (Fidan, 2020). Due to the embryonic state of the literature on this new market, contradictory findings can be observed about the nature of Bitcoin, especially during times of turmoil such as Covid-19 pandemic. Although almost all cryptocurrencies are used, traded or utilized globally, the existing studies mainly take Bitcoin into consideration, causing Bitcoin literature to grow rapidly while other cryptocurrencies remain relatively undiscovered. One of the main contributions of this study is therefore to explore the nature of other main cryptocurrencies, besides Bitcoin.

The characteristics and relationship between cryptocurrencies and financial assets were explored with various methods, such as sequential monitoring test (Ji et al., 2020), downside risk measurement (Conlon, & McGee, 2020), regression analysis (Hu et al., 2019), DCC model (Stensas et al., 2019; Urquhart, & Zhang, 2019) and GARCH model (Klein et al., 2018; Naeem et al., 2020). These methods were utilized to compare cryptocurrencies against stock markets (Shahzad et al., 2020; Lahmiri, and Bekiros, 2020), gold (Dyhrberg, 2016; Ji et al., 2019; Frankovic et al., 2021), oil (Okorie and Lin, 2020; Adekoya, and Oliyide, 2021), general commodity (Bouri et al., 2017b) and US dollar index (Mokni and Ajmi, 2021). Only a few of these studies considered volatility spillover and shock transmission effects, and there is a clear need for more studies that investigate the volatility spillovers between cryptocurrencies and financial assets (Bouri et al., 2018). On the other hand, the studies that investigated spillovers between these financial assets and cryptocurrencies concluded that there are bidirectional volatility spillovers between Bitcoin and S&P 500 (Ghorbel and Jeribi, 2021), bidirectional volatility spillovers between Bitcoin and MSCI emerging markets (Bouri et al., 2018), unidirectional spillovers between Bitcoin and FTSE 100 (Aydoğan et al., 2022) and unidirectional spillovers between Bitcoin and Nikkei 225 (Van de Klashorst, 2018). When cryptocurrencies and stock markets are compared, the presence of return and shock spillovers suggest the movement of investors across markets; searching for alternative assets or exiting current stocks where Bitcoin is often perceived as an alternative asset. Unidirectional shock spillovers from DAX 30, FTSE 100 and Nikkei 225 imply that the investors migrate to the bitcoin market as a hedge against future shocks (Uzonwanne, 2021). In line with Uzonwanne (2021), Ustaoğlu (2022) found a unidirectional shock transmission from BIST100 to Bitcoin, Ripple and Litecoin, and a unidirectional volatility spillover from BIST100 to Bitcoin and Ethereum. This finding is also persistent with the prior studies mentioned above. In the case of cryptocurrencies and gold, a bidirectional volatility spillover between cryptocurrencies and gold is observed. Furthermore, when investors leave stock markets, they often use gold and bitcoin as a hedge in the presence of volatility spillovers (Ghorbel and Jeribi, 2021). Although cryptocurrencies and traditional currencies were found out to be not correlated, during a global turmoil, significant volatility spillover effects are observed between the returns of cryptocurrencies and traditional currencies including EUR, RUB, GBP, JPY, CNY and DXY. During US-China trade war, the COVID-19 pandemic and the Russia-Ukraine war, investors considered especially Bitcoin a safe haven against EUR (Hsu, 2022).

While the majority of studies focus on Bitcoin versus financial assets, a smaller number of studies analyzing the relationship between financial assets and main cryptocurrencies such as Ethereum, Litecoin, Ripple and Tether. Gil-Alana et al. (2020) studied the diversifier properties of 6 major cryptocurrencies and stock indices using ARFIMA model and concluded that cryptocurrencies are decoupled from the financial assets confirming the new investment and asset class property of cryptocurrencies. Büberkökü (2021) examined the volatility spillover effects of five major cryptocurrencies including Bitcoin, Binance coin, Bitcoin cash, Stellar and Chainlink using Cheung and Ng's (1996) test. Although the objective may seem similar, our study focuses on a different set of altcoins using a different methodology utilizing bivariate MGARCH with the BEKK specifications. Another research carried by Goodell and Goutte (2020) investigated the safe haven features of cryptocurrencies involving major cryptocurrencies against stock markets. Using the wavelet coherence method, they concluded that Bitcoin and Tether exhibit as a safe haven against stock markets, unlike other cryptocurrencies. While the studies mentioned above investigate the relationship between major cryptocurrencies and financial assets, a number of research in the literature have concentrated on the return and volatility of cryptocurrencies (Dyhrberg, 2016; Balcilar et al., 2017; Bariviera, 2017; Bouri et al., 2017a; Chaim and Laurini, 2018; Koutmos, 2018; Charles and Darné, 2019; Aysan et al., 2019; Katsiampa, 2018a, 2019; Katsiampa et al., 2019; Silva et al., 2019, Malladi and Dheeriya, 2021, Foroutan and Lahmiri (2022). However, only a few studies concentrate on the volatility dynamics in terms of volatility spillovers. Existing studies exploring the volatility spillovers between cryptocurrencies use the dataset for the years 2015-2018 (Katsiampa et al., 2019; Kumar and Anandarao, 2019, Beneki et al. 2019). Katsiampa et al. (2019) found the presence of bidirectional volatility spillover effects between all pairs of Bitcoin, Ethereum and Litecoin, unidirectional shock spillovers from Ethereum to Litecoin and bidirectional shock transmission effects between Bitcoin and both Ethereum and Litecoin. Similarly, Kumar and Anandarao (2019) investigated the dynamics of volatility spillover across only Bitcoin, Ethereum, Ripple and Litecoin. The results revealed that volatility spillover is influenced by shocks in Bitcoin prices and other exogenous events. Beneki et al. (2019) analyzed the volatility spillover effects and hedging abilities between Bitcoin and Ethereum. Similarly, Gemici and Polat (2021) used causality-in-mean and causality-in-variance tests among cryptocurrencies, however, they also analyzed only Bitcoin, Ethereum and Litecoin. As shown, the prior studies focusing on volatility spillovers between cryptocurrencies analyze a few main cryptocurrencies such as Bitcoin, Ethereum, Ripple and Litecoin leaving other major cryptocurrencies unexplored. The rapid global developments in the cryptocurrency market and the emergence of new cryptocurrencies highlight the need for a more comprehensive and up-to-date study. Thus, this study tries to fill the gap by using a recent dataset covering the period 2018-2021 and conducting research on volatility spillover and shock transmission effects between eight major cryptocurrencies, BTC, ETH, LTC, XRP, XLM, BCH, ADA and EOS. Furthermore, we also observe the shifts in receiver/transmitter roles and shock transmissions of these major cryptocurrencies compared to past studies.

3. Data

In order to measure return and volatility spillover effects among cryptocurrencies, the daily prices for eight major cryptocurrencies, BTC, ETH, LTC, XRP, XLM, BCH, ADA and EOS are used. These cryptocurrencies are selected according to the highest market capitalization, as well as trading volume compared to other assets in the cryptocurrency market. Since the market capitalization of both BTC and ETH represents more than 60 % of the total market capitalization in the cryptocurrency market as of September 7, 2021, it is therefore considered representative of the whole currency market[2]. Moreover, since some cryptocurrencies rapidly disappear quickly, these may not be traded for a long period. The selected eight currencies have been chosen publicly trade for almost three consecutive years. In addition to the size and liquidity of these cryptocurrencies in the market, popularity is another factor behind their inclusion in our sample set. The sample period spans from June 1, 2018 to September 7, 2021, covering a total of 1195 daily observations. This period is chosen due to the coverage of different trends and investment behaviors in the cryptocurrency market. The data for all these cryptocurrencies are

[2] See https://coinmarketcap.com for more information.

extracted from CoinMarketCap[3]. The closing price returns of cryptocurrencies in the sample are calculated by taking the first difference in log prices.

Table 1 presents a wide range of summary statistics of all the sampled cryptocurrencies, with the Jarque-Bera (JB) normality analysis. The average market return is positive for all cryptocurrencies except EOS. The negative average mean return is of particular interest as it demonstrates high volatility of returns on both sides of the mean in EOS market. Among the return series, ADA represents the highest mean (0.223%), followed by BTC (0.171%) and ETH (0.152%), while BCH has the lowest positive mean return (0.011%). Regarding the volatility of cryptocurrencies in the market, standard deviations range from (3.742%) for BTC, too (5.957%) for ADA.

Table 1: Descriptive Statistics

	Mean	Median	Std.Dev.	Skewness	Kurtosis	JB	Q(20)	ARCH
BTC	0.00171	0.00163	0.03742	-0.49012	9.57895	2147.655*	22689*	6.219*
ETH	0.00152	0.00149	0.04955	-0.73472	9.82855	2368.274*	22346*	8.716*
LTC	0.00035	0.00034	0.05237	-0.58794	8.95142	1786.439*	21369*	8.831*
XRP	0.00061	-0.00048	0.05712	0.30201	13.6889	5563.783*	19054*	11.867*
XLM	0.00029	-0.00034	0.05661	0.66331	10.3978	2742.019*	21726*	8.799*
BCH	0.00011	0.00071	0.05946	-0.02592	12.6108	4483.860*	19296*	6.486*
ADA	0.00223	0.00000	0.05957	-0.00890	6.96875	764.5957*	21672*	11.699*
EOS	-0.00081	0.00137	0.05930	-0.32612	8.99169	1763.315*	17538*	13.833*

Note: Q(20) represents the 20th-lagged Ljung-Box Q statistics. ARCH shows the LM test results for conditional variance. * indicates statistical significance at the 1% level.

Moreover, the detailed information related to the data reveals that all the cryptocurrency series are negatively skewed, except for XRP and XLM and not perfectly symmetrical. The kurtosis of all cryptocurrencies in the sample is greater than three, indicating that each variable has typical characteristics of leptokurtosis and fat tail. It is known that these two are the typical characteristics of financial time series data. Furthermore, the JB test statistics of each variable is significant from zero, confirming the rejection of the null hypothesis of normality at 1% statistical significance level in all series. The ARCH test results indicate that there is a conditional variance in all variables. The Ljung-Box Q statistic represents that each variable has the same significant phenomenon of autocorrelation.

Before applying VAR-BEKK-GARCH model, it is vital to test whether the series are stationary. Therefore, the Augmented Dickey-Fuller (ADF) unit root tests are employed to check the stationarity of the variables. The test results, represented in Table 2, indicate that all series are stationary in their first differences. To conclude, all the time series properties of the variables for the cryptocurrencies in the sample suggest that GARCH family models will be appropriate for this study due to the heteroscedasticity and the VAR enhanced BEKK-GARCH models will be fitted well to the data.

[3] The dataset is obtained from https://coinmarketcap.com/tr/.

Table 2: Unit Root Test Results

Variable	Level		1st Difference	
	ADF		ADF	
	Constant	Constant Trend	Constant	Constant Trend
BTC	0.257	-1.910	-35.436*	-35.492*
ETH	0.560	-2.062	-35.446*	-35.667*
LTC	-1.304	-2.335	-34.891*	-34.928*
XRP	-1.378	-1.876	-31.567*	-31.622*
XLM	-1.067	-1.532	-34.028*	-34.098*
BCH	-2.248	-2.593	-32.637*	-32.681*
ADA	1.068	-1.368	-35.375*	-35.635*
EOS	2.306	-2.111	-36.213*	-36.243*

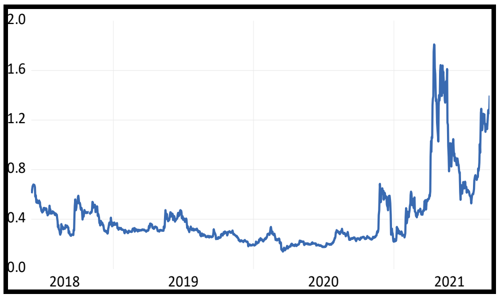
* indicates statistical significance at the 1% level.

Figure 1. Daily Closing Price of Cryptocurrencies over the period

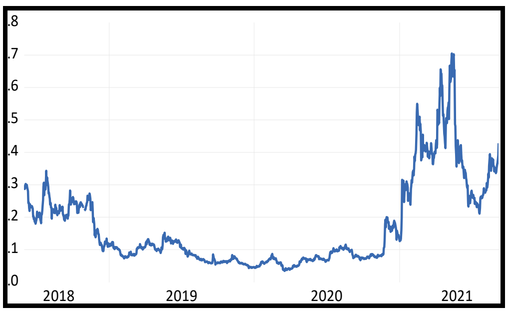
June 1, 2018–September 7, 2021

(i) Bitcoin **(ii)**

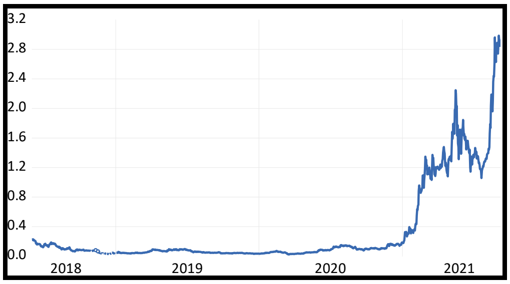
Ethereum



(iii) Litecoin **(iv) Ripple**



(v) Stellar **(vi) Bitcoin Cash**



(vii) Cardano

(viii) EOS

Figure 1 presents the daily closing price data from the selected eight cryptocurrencies. We observe a relatively stable trend from the period September 2018 to January 2020 for most of the cryptocurrencies. Then, all closing prices of cryptocurrencies show an increasing trend. This period coincides with the COVID-19 pandemic period when the governments intervened to protect their economies, and Central Banks took powerful steps to provide liquidity and restore the credit flow. Due to these programs, the liquidity injections to the money and capital markets were likely to generate asset bubbles and volatilities in the financial markets. The graphical representation of the data in this figure, which explains the possible co-movements between them, indicates that their fluctuation patterns are similar, and thus could be correlated over time. Moreover, the correlation matrix for the pairs of cryptocurrencies, represented in Table 3, confirms the existence of a positive and high degree of correlation at 1% significance level. Table 3 shows that the highest correlation is observed between ADA-ETH with a correlation coefficient of 97%, followed by BTC-ETH (93%) while the lowest correlation is found between BTC-EOS with a correlation coefficient of 19%. In this vein, these correlations shed light on the connections in the crypto market which leads us to analyze return and volatility spillovers among cryptocurrencies.

Table 3. Pairwise Correlation Matrix

	BTC	**ETH**	**LTC**	**XRP**	**XLM**	**BCH**	**ADA**	**EOS**
BTC	1							
ETH	0.931757 (0.000)*	1						
LTC	0.846541 (0.000)*	0.871736 (0.000)*	1					
XRP	0.606542 (0.000)*	0.764250 (0.000)*	0.769281 (0.000)*	1				
XLM	0.641183 (0.000)*	0.799997 (0.000)*	0.762013 (0.000)*	0.864968 (0.000)*	1			
BCH	0.616069 (0.000)*	0.728664 (0.000)*	0.793378 (0.000)*	0.706458 (0.000)*	0.765050 (0.000)*	1		
ADA	0.885430 (0.000)*	0.976528 (0.000)*	0.852714 (0.000)*	0.804092 (0.000)*	0.845688 (0.000)*	0.708994 (0.000)*	1	
EOS	0.190152 (0.000)*	0.381184 (0.000)*	0.606897 (0.000)*	0.664255 (0.000)*	0.619792 (0.000)*	0.811719 (0.000)*	0.416084 (0.000)*	1

* indicates statistical significance at the 1% level.

4. Methodology

GARCH models, proposed by Bollerslev (1986), are widely used to model volatility, as well as variability of financial times series data. With the univariate or multivariate types of GARCH model, previous volatility estimations may affect the future variance. Due to the limitations of the univariate models, multivariate GARCH (MGARCH) models have been widely employed to explore the spillover effects between variables.

The joint evolution of return and volatility spillover effects among selected cryptocurrencies is conducted by using MGARCH model with BEKK specification. Proposed by Engle and Kroner (1995), this model requires the positive estimated variance-covariance matrix, and therefore appears to be the most suitable for the assessment of the dynamics of the conditional volatility and volatility interdependence among the cryptocurrency returns. This model has three main advantages which allow for cross-sectional dynamics, specify volatility spillover, and moreover, provide detailed directions within the revealed spillover effects.

The conditional mean equation is modeled based on a Vector Autoregressive (VAR) model. VAR (1) model is chosen according to the minimum Akaike Information criterion values.

The mean equation is defined as:

$$R_t = \mu + \sum_{i=1}^{k} \gamma_i R_{t-i} + \varepsilon_t \tag{1}$$

where $R_t = (R_{1t}, R_{2t})"$ is the return for one of the cryptocurrency assets, $\mu = (\mu_1, \mu_2)"$ is a 2-vector of the constant term, and $\varepsilon_t = (\varepsilon_{1t}, \varepsilon_{2t})"$ is the error term for one of the cryptocurrency asset's returns.

The conditional variance-covariance matrix of the BEKK model, H_t, is expressed as follows:

$$H_t = CC' + A'(\varepsilon_{t-1}\varepsilon'_{t-1})A + B'H_{t-1}B \tag{2}$$

where $\varepsilon_t = \begin{pmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{pmatrix}$ is the error terms from the mean equation.

$H_t = \begin{pmatrix} h_{11,t} & h_{12,t} \\ h_{21,t} & h_{22,t} \end{pmatrix}$ is the conditional variance-covariance matrix and $C = \begin{pmatrix} c_{11} & 0 \\ c_{21} & c_{22} \end{pmatrix}$ is the lower triangular matrix. A= $\begin{pmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{pmatrix}$ and $B = \begin{pmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{pmatrix}$ are both 2x2 square matrix of parameters. $h_{12,t}$ and $h_{2,1\,,t}$ are the conditional covariance between two cryptocurrencies.

ARCH coefficients, a_{11}, a_{22} of A matrix reflect the impact of a past shock on the volatility of the same variable. GARCH coefficients, b_{11}, b_{22} of B matrix reflect the continuous characteristics of the fluctuation and the degree of volatility persistence. The off-diagonal elements, a_{12} and a_{21}, of A matrix refer to the impact conduction effects of different cryptocurrencies; while the off-diagonal elements, b_{12} and b_{21}, of B matrix refer to the shock and volatility spillover effect of different cryptocurrencies.

5. Empirical Results

The estimation results of the multivariate VAR-BEKK-GARCH model for eight cryptocurrencies, BTC, ETH, LTC, XRP, XLM, BCH, ADA and EOS are represented in Tables 4, 6, 8, 10, 12, 14, 16, 18 while Table 5, 7, 9, 11, 13, 15, 17, and 19 summarize the estimated results of pair-wise models.

Taking a close look at the mean equation, the findings in the summarized tables indicate the existence of the highest bidirectional mean spillovers between the pairs ADA and other cryptocurrencies, and the lowest bidirectional spillover between the pairs ETH and other cryptocurrencies. Moreover, for all the cryptocurrency pairs considered, there is no mean volatility spillover for 7 cryptocurrency pairs: BCH - EOS, BCH - XLM, BTC - ETH, EOS - XLM, ETH - LTC, ETH - XRP, XLM - XRP. Overall, it is observed that there exist return spillovers between the pairs, with the exception of the previously mentioned 7 pairs, implying that the lagged values of one cryptocurrency's return significantly affect the current return of others.

Turning to the conditional variance equation, the diagonal parameters, a_{ii} and b_{ii}, are statistically significant, suggesting that a cryptocurrency's current volatility is significantly affected by both its own past shocks and volatility. Moreover, the off-diagonal elements, a_{ij} and b_{ij}, are statistically significant, indicating evidence of significant cross-market effects between the cryptocurrency pairs. As for shock and volatility spillovers, more specifically, the highest bidirectional cross-market effects are observed for 5 pairs of each of the cryptocurrencies, namely, BCH, ETH and XRP, while the least bidirectional effects are found between the pairs BTC and 2 other cryptocurrencies, and XLM and 2 other cryptocurrencies. It is also noteworthy that among all cryptocurrency pairs, there is bidirectional volatility spillover effects between XRP and all other cryptocurrencies.

When the results are evaluated in terms of volatility spillover effects, volatility spillover effects between BTC and major cryptocurrencies seem to remain in the past years, and we observed a shift in Ethereum's behavior when compared to past studies. Kumar and Anandarao (2019) analyzed the volatility spillover effects between major cryptocurrencies considering the period of 2015-2018, suggesting high volatility spillover effects between BTC- LTC, BTC- XRP, XRP - LTC and moderate volatility spillover effects between ETH - LTC and ETH - XRP. Another study conducted by Katsiampa et al. (2019) identified bidirectional volatility spillover effects between BTC and both ETH and LTC. With the exception of the results of ETH pairs, these findings concur with our findings. Ethereum's change in nature might be due to the significant increase in its market capitalization, especially after 2018.

Table 4. Estimated results of volatility spillover between ADA and other cryptocurrencies based on VAR-BEKK-GARCH model

	ADA-BCH	ADA- BTC	ADA- EOS	ADA-ETH	ADA-LTC	ADA-XLM	ADA-XRP
Panel A. Mean Equation							
$\delta(1)_{11}$	1.003	0.995	1.002	0.978	0.997	1.007	1.006
	[628.782]*	[364.423]*	[699.922]	[163.311]*	[1140.356]*	[405.263]*	[474.627]*
$\delta(1)_{12}$	-0.008	0.009	-0.012	0.029	0.009	-0.012	-0.017
	[-2.182]**	[2.137]**	[-3.259]*	[3.881]*	[4.679]*	[-2.805]*	[-3.282]*
μ_1	0.060	-0.095	0.022	-0.215	-0.046	-0.008	-0.002
	[2.394]**	[-2.048]**	[3.263]	[-3.773]*	[-4.905]*	[-1.499]	[-0.739]
$\delta(1)_{21}$	0.002	0.000	0.000	0.007	0.002	0.004	0.003
	[1.671]***	[0.319]	[0.581]*	[1.478]	[2.236]**	[2.182]**	[1.914]**
$\delta(1)_{22}$	0.991	1.000	0.989	0.992	0.995	0.988	0.988
	[232.624]*	[333.695]*	[198.493]*	[168.618]*	[546.103]*	[251.935]*	[257.551]*
μ_2	0.053	-0.000	0.012	0.062	0.025	-0.013	-0.007
	[1.948]**	[-0.006]	[1.570]*	[1.405]	[2.867]*	[-2.531]**	[-2.017]**
Panel B. Variance Equation							
c_{11}	0.039	-0.023	-0.030	-0.032	0.008	-0.028	-0.023
	[15.669]*	[-11.240]*	[-13.348]*	[-11.970]*	[4.032]*	[-12.430]*	[-12.245]*
c_{21}	-0.005	-0.014	-0.001	0.008	0.031	-0.025	-0.019
	[-1.703]***	[-8.755]*	[-0.114]	[3.102]*	[14.813]*	[-10.347]*	[-8.572]*
c_{22}	0.000	0.009	0.020	-0.000	-0.000	0.012	-0.011
	[0.000]	[12.233]*	[4.005]*	[-0.004]	[-0.001]	[12.249]*	[-11.883]*
a_{11}	-0.174	0.365	0.257	-0.264	0.270	0.303	0.355
	[-3.860]*	[11.619]*	[7.469]*	[-7.033]*	[7.594]*	[5.849]*	[9.816]*
a_{12}	0.083	-0.162	0.025	0.057	-0.160	-0.264	-0.208
	[2.696]*	[-5.630]*	[0.720]	[1.849]***	[-4.583]*	[-5.363]*	[-5.152]*
a_{21}	-0.719	-0.003	0.797	-0.759	0.669	0.099	0.129
	[-15.030]*	[-0.312]	[18.190]*	[-16.482]*	[16.641]*	[1.728]	[3.267]*
a_{22}	0.021	0.533	0.009	0.008	0.071	0.672	0.825
	[0.533]	[15.319]*	[0.204]	[0.231]	[2.016]**	[11.836]*	[16.447]*
b_{11}	0.055	0.908	0.437	0.269	0.721	0.908	0.889
	[0.404]	[48.373]*	[7.949]*	[4.485]*	[28.359]*	[35.058]*	[51.801]*
b_{12}	-0.387	0.075	0.275	-0.311	0.257	0.109	0.053
	[-4.050]*	[5.450]*	[5.994]*	[-6.736]*	[8.333]*	[4.294]*	[2.472]**
b_{21}	0.272	-0.167	-0.073	0.377	-0.361	-0.193	-0.125
	[4.572]*	[-4.403]*	[-0.614]	[9.167]*	[-11.855]*	[-4.020]*	[-5.516]*
b_{22}	0.956	0.712	0.835	0.944	0.669	0.623	0.655
	[37.321]*	[26.838]*	[16.755]*	[70.835]*	[14.762]*	[13.368]*	[22.533]*

Notes:1. μ_1 and $\mu_2$are constant term of the mean equations. 2. $\delta(1)_{11}$ and $\delta(1)_{22}$ capture variables' own lagged effects in mean, in which variable 1 denotes ADA *2* denotes BCH, BTC, EOS, ETH, LTC, XLM and XRP, respectively 3. $\delta(1)_{12}$ stands for lagged spillover effects in mean from ADA to BCH, BTC, EOS, ETH, LTC, XLM and XRP, and $\delta(1)_{21}$ indicates the same effect in the opposite direction. 4. c_{11}, $c_{21}$and c_{22} are constant terms of the variance equations. 5. a_{11} and a_{22} represent the ARCH effect in two variables. 6. a_{12} measures the spillover effect of a previous shock in ADA on the current volatility of BCH, BTC, EOS, ETH, LTC, XLM and XRP, and a_{21} measures the spillover effect in the opposite direction. 7. $b_{11}$and b_{22}indicate the GARCH terms, which measure volatility persistence of each series. 8. b_{12} measures the spillover effect of the last period's variance of ADA on the current variance of BCH, BTC, EOS, ETH, LTC, XLM and XRP, and b_{21} measures the spillover effect in the opposite direction. 9. Numbers in square brackets correspond to t-statistics. * , ** and *** indicate statistical significance at the 1%, 5% and 10% level respectively.

Table 5. Summary of estimated results for the conditional mean and conditional variance equations between ADA and other cryptocurrencies

	BCH	BTC	EOS	ETH	LTC	XLM	XRP	
Panel A. Mean spillovers								
ADA	↔	→	↔	→	↔	↔	↔	5 bidirectional 2 unidirectional
Panel B. Shock Transmission								
ADA	↔	→	←	↔	↔	→	↔	4 bidirectional 3 unidirectional
Panel C. Volatility Spillovers								
ADA	↔	↔	→	↔	↔	↔	↔	6 bidirectional 1 unidirectional

Notes: ↔, → or ←, - indicate bidirectional, unidirectional, and no volatility transmission, respectively. ← means the related commodity on the first column is volatility receiver while → is the indication of volatility transmitter.

Table 6. Estimated results of volatility spillover between BCH and other cryptocurrencies based on VAR-BEKK-GARCH model

	BCH-ADA	BCH-BTC	BCH-EOS	BCH-ETH	BCH-LTC	BCH-XLM	BCH-XRP
Panel A. Mean Equation							
$\delta(1)_{11}$	1.003	0.972	0.995	0.989	0.986	0.993	0.978
	[628.782]*	[492.047]*	[183.092]*	[427.678]*	[316.774]*	[210.456]*	[216.290]*
$\delta(1)_{12}$	-0.008	0.012	-0.001	0.003	0.009	0.002	0.012
	[-2.182]**	[8.138]*	[-0.173]	[2.956]	[2.430]**	[0.661]	[2.733]*
μ_1	0.060	0.031	0.026	0.041	0.036	0.040	0.131
	[2.394]**	[2.108]**	[1.063]	[4.572]*	[5.407]*	[1.235]	[4.434]*
$\delta(1)_{21}$	0.002	-0.004	0.000	-0.008	-0.011	0.003	0.001
	[1.671]***	[-2.603]*	[0.038]	[-17.307]*	[-4.136]*	[0.725]	[0.308]
$\delta(1)_{22}$	0.991	1.002	0.989	1.004	1.007	0.996	0.992
	[232.624]*	[746.896]*	[135.352]*	[2654.274]*	[283.029]*	[294.501]*	[258.268]*
μ_2	0.053	0.008	0.012	0.026	0.039	-0.026	-0.015
	[1.948]**	[0.779]	[0.452]	[9.547]*	[4.311]*	[-0.817]	[-0.730]
Panel B. Variance Equation							
c_{11}	0.039	0.054	0.020	0.018	-0.019	0.022	-0.017
	[15.669]*	[38.000]*	[11.839]*	[11.236]*	[-10.351]*	[5.894]*	[-7.564]*
c_{21}	-0.005	0.003	0.014	0.018	-0.019	0.011	-0.010
	[-1.703]***	[0.588]	[8.372]*	[7.827]*	[-9.647]*	[1.791]**	[-6.487]*
c_{22}	0.000	-0.010	-0.007	-0.013	0.010	0.019	-0.000
	[0.000]	[-1.797]**	[-5.815]*	[-12.768]*	[9.222]*	[3.902]*	[-0.000]
a_{11}	-0.174	0.061	0.526	0.462	0.536	0.000	0.084
	[-3.860]*	[2.075]**	[47.008]*	[10.305]*	[15.031]*	[0.000]	[2.875]
a_{12}	0.083	0.708	-0.003	-0.143	-0.019	0.674	0.597
	[2.696]*	[24.274]*	[-5.560]*	[-5.496]*	[-0.529]	[16.537]*	[17.949]*
a_{21}	-0.719	-0.008	-0.166	-0.195	-0.322	-0.087	-0.120
	[-15.030]*	[-0.365]	[-5.873]*	[-4.526]*	[-7.445]*	[-2.293]**	[-4.059]*
a_{22}	0.021	0.053	0.261	0.405	0.284	0.374	0.410
	[0.533]	[1.919]**	[10.359]*	[13.862]*	[7.191]*	[11.053]*	[14.718]*
b_{11}	0.055	0.443	0.845	0.961	0.888	0.790	0.891
	[0.404]	[17.022]*	[138.061]*	[53.600]*	[71.814]*	[18.957]*	[39.089]*
b_{12}	-0.387	-0.079	0.026	0.190	0.074	-0.196	-0.155
	[-4.050]*	[-0.454]	[20.144]*	[11.709]*	[3.901]*	[-5.759]*	[-8.869]*
b_{21}	0.272	-0.002	0.028	-0.116	-0.000	0.403	0.238
	[4.572]*	[-0.182]	[2.053]**	[-4.529]*	[-0.016]	[8.566]*	[6.733]*
b_{22}	0.956	0.288	0.901	0.648	0.798	0.497	0.674
	[37.321]*	[7.563]*	[73.462]*	[21.834]*	[40.304]*	[9.380]*	[28.272]*

See Notes to Table 4.

Table 7. Summary of estimated results for the conditional mean and conditional variance equations between BCH and other cryptocurrencies

	ADA	BTC	EOS	ETH	LTC	XLM	XRP	
Panel A. Mean spillovers								
BCH	↔	↔	-	←	↔	-	→	3 bidirectional 2 unidirectional 2 no spillover
Panel B. Shock Transmission								
BCH	↔	→	↔	↔	←	↔	↔	5 bidirectional 2 unidirectional
Panel C. Volatility Spillovers								
BCH	↔	-	↔	↔	↔	↔	↔	6 bidirectional 1 no spillover

See Notes to Table 5.

Table 8. Estimated results of volatility spillover between BTC and other cryptocurrencies based on VAR-BEKK-GARCH model

	BTC-ADA	BTC-BCH	BTC-EOS	BTC-ETH	BTC-LTC	BTC-XLM	BTC-XRP
Panel A. Mean Equation							
$\delta(1)_{11}$	0.995	0.972	1.002	0.997	0.997	1.001	1.003
	[364.423]*	[492.047]*	[931.742]*	[334.660]*	[529.954]*	[2247.466]*	[4703.876]*
$\delta(1)_{12}$	0.009	0.012	-0.002	0.003	0.004	-0.002	-0.005
	[2.137]**	[8.138]*	[-1.004]	[1.308]	[1.722]***	[-1.960]**	[-6.558]*
μ_1	-0.095	0.031	-0.015	0.010	0.007	-0.016	0.114
	[-2.048]**	[2.108]**	[-1.530]	[0.667]	[0.698]	[-4.584]*	[12.144]*
$\delta(1)_{21}$	0.000	-0.004	0.003	-0.004	-0.001	0.005	0.017
	[0.319]	[-2.603]*	[2.681]*	[-0.944]	[-0.649]	[2.855]*	[10.055]*
$\delta(1)_{22}$	1.000	1.002	0.987	1.002	0.999	0.994	0.992
	[333.695]*	[746.896]*	[534.250]*	[305.054]*	[275.031]*	[395.314]*	[1188.880]*
μ_2	-0.000	0.008	-0.014	0.025	0.017	-0.063	-0.108
	[-0.006]	[0.779]	[-1.167]	[1.050]	[1.248]	[-3.072]*	[-8.530]*
Panel B. Variance Equation							
c_{11}	-0.023	0.054	-0.019	0.013	-0.017	0..016	0.002
	[-11.240]*	[38.000]*	[-28.385]*	[6.674]*	[-16.763]*	[11.554]*	[9.201]*
c_{21}	-0.014	0.003	-0.002	-0.007	-0.011	0.013	0.000
	[-8.755]*	[0.588]	[-1.607]***	[-0.967]	[-1.150]	[4.941]*	[0.529]
c_{22}	0.009	-0.010	0.017	-0.017	-0.024	0.018	0.010
	[12.233]*	[-1.797]**	[9.271]*	[-3.051]*	[-11.230]*	[13.622]*	[13.615]*
a_{11}	0.365	0.061	0.096	-0.039	0.011	0.427	0.450
	[11.619]*	[2.075]**	[3.873]*	[-1.361]	[0.392]	[8.780]*	[18.630]*
a_{12}	-0.162	0.708	-0.046	0.113	0.019	-0.246	-0.002
	[-5.630]*	[24.274]*	[-16.230]*	[2.574]*	[0.360]	[-3.811]*	[-0.757]
a_{21}	-0.003	-0.008	-0.617	-0.685	-0.634	-0.042	0.026
	[-0.312]	[-0.365]	[-23.540]*	[-24.247]*	[-24.238]*	[-1.341]	[4.795]*
a_{22}	0.533	0.053	0.233	0.034	0.013	0.541	0.490
	[15.319]*	[1.919]**	[10.352]*	[1.001]	[0.392]	[13.019]*	[26.365]*
b_{11}	0.908	0.443	0.060	0.269	0.180	0.758	0.920
	[48.373]*	[17.022]*	[1.224]	[7.260]*	[3.857]*	[22.779]*	[133.675]*
b_{12}	0.075	-0.079	-0.036	-0.373	-0.474	0.066	0.002
	[5.450]*	[-0.454]	[-18.888]*	[-6.427]*	[-7.695]*	[3.973]*	[3.301]*
b_{21}	-0.167	-0.002	0.079	0.176	0.016	0.059	-0.012
	[-4.403]*	[-0.182]	[8.462]*	[3.831]*	[0.202]	[2.149]**	[-3.404]*
b_{22}	0.712	0.288	0.923	0.882	0.805	0.772	0.863
	[26.838]*	[7.563]*	[77.869]*	[34.279]*	[13.680]*	[30.694]*	[81.933]*

See Notes to Table 4.

Table 9. Summary of estimated results for the conditional mean and conditional variance equations between BTC and other cryptocurrencies

	ADA	BCH	EOS	ETH	LTC	XLM	XRP	
Panel A. Mean spillovers								
BTC	→	↔	←	-	↔	↔	↔	4 bidirectional 2 unidirectional 1 no spillover
Panel B. Shock Transmission								
BTC	→	→	↔	↔	←	→	←	2 bidirectional 5 unidirectional
Panel C. Volatility Spillovers								
BTC	↔	-	↔	↔	→	↔	↔	5 bidirectional 1 unidirectional 1 no spillover

See Notes to Table 5.

Table 10. Estimated results of volatility spillover between EOS and other cryptocurrencies based on VAR-BEKK-GARCH model

	EOS-ADA	EOS-BCH	EOS-BTC	EOS-ETH	EOS-LTC	EOS-XLM	EOS-XRP
Panel A. Mean Equation							
$\delta(1)_{11}$	1.002	0.995	1.002	0.987	0.982	0.983	0.999
	[699.922]	[183.092]*	[931.742]*	[235.169]*	[195.517]*	[187.971]*	[218.300]*
$\delta(1)_{12}$	-0.012	-0.001	-0.002	0.001	0.006	0.002	-0.003
	[-3.259]*	[-0.173]	[-1.004]	[0.656]	[1.633]***	[0.784]	[-0.968]
μ_1	0.022	0.026	-0.015	0.010	-0.003	0.021	-0.007
	[3.263]	[1.063]	[-1.530]	[0.962]	[-0.275]	[1.820]**	[-0.887]
$\delta(1)_{21}$	0.000	0.000	0.003	-0.012	-0.014	-0.001	0.011
	[0.581]*	[0.038]	[2.681]*	[-3.188]*	[-3.157]*	[-0.357]	[2.953]*
$\delta(1)_{22}$	0.989	0.989	0.987	1.002	1.004	0.996	0.987
	[198.493]*	[135.352]*	[534.250]*	[666.706]*	[275.965]*	[368.026]*	[277.834]*
μ_2	0.012	0.012	-0.014	0.001	-0.000	-0.007	-0.030
	[1.570]*	[0.452]	[-1.167]	[0.171]	[-0.037]	[-0.662]	[-3.632]*
Panel B. Variance Equation							
c_{11}	-0.030	0.020	-0.019	0.018	0.020	-0.018	-0.028
	[-13.348]*	[11.839]*	[-28.385]*	[8.432]*	[10.172]*	[-4.753]*	.[-11.028]*
c_{21}	-0.001	0.014	-0.002	0.017	0.019	-0.001	0.011
	[-0.114]	[8.372]*	[-1.607]***	[6.264]*	[7.204]*	[-0.197]	[7.795]*
c_{22}	0.020	-0.007	0.017	-0.012	-0.011	0.026	-0.000
	[4.005]*	[-5.815]*	[9.271]*	[-13.752]*	[-7.568]*	[11.707]*	[-0.000]
a_{11}	0.257	0.526	0.096	0.430	0.429	-0.005	-0.195
	[7.469]*	[47.008]*	[3.873]*	[9.788]*	[11.534]*	[-0.128]	[-5.234]*
a_{12}	0.025	-0.003	-0.046	-0.101	-0.115	0.768	0.749
	[0.720]	[-5.560]*	[-16.230]*	[-2.427]**	[-3.014]*	[18.266]*	[22.283]*
a_{21}	0.797	-0.166	-0.617	-0.194	-0.257	-0.025	0.012
	[18.190]*	[-5.873]*	[-23.540]*	[-3.888]*	[-8.949]*	[-0.708]	[0.408]
a_{22}	0.009	0.261	0.233	0.435	0.305	0.353	0.420
	[0.204]	[10.359]*	[10.352]*	[9.147]*	[8.019]*	[8.829]*	[15.397]*
b_{11}	0.437	0.845	0.060	0.913	0.949	0.869	0.791
	[7.949]*	[138.061]*	[1.224]	[42.708]*	[57.474]*	[28.963]*	[23.321]*
b_{12}	0.275	0.026	-0.036	0.131	0.176	-0.054	0.130
	[5.994]*	[20.144]*	[-18.888]*	[5.108]*	[7.382]*	[-1.020]	[7.608]*
b_{21}	-0.073	0.028	0.079	-0.025	-0.085	0.299	0.257
	[-0.614]	[2.053]**	[8.462]*	[-0.820]	[-4.745]*	[6.866]*	[9.774]*
b_{22}	0.835	0.901	0.923	0.713	0.707	0.367	0.544
	[16.755]*	[73.462]*	[77.869]*	[18.659]*	[17.574]*	[7.237]*	[18.530]*

See Notes to Table 4.

Table 11. Summary of estimated results for the conditional mean and conditional variance equations between EOS and other cryptocurrencies

	ADA	BCH	BTC	ETH	LTC	XLM	XRP	
Panel A. Mean spillovers								
EOS	↔	-	←	←	↔	-	←	2 bidirectional 3 unidirectional 2 no spillover
Panel B. Shock Transmission								
EOS	←	↔	↔	↔	↔	→	→	4 bidirectional 3 unidirectional
Panel C. Volatility Spillovers								
EOS	→	↔	↔	→	↔	←	↔	4 bidirectional 3 unidirectional

See Notes to Table 5.

Table 12. Estimated results of volatility spillover between ETH and other cryptocurrencies based on VAR-BEKK-GARCH model

	ETH-ADA	ETH-BCH	ETH-BTC	ETH-EOS	ETH-LTC	ETH-XLM	ETH-XRP
Panel A. Mean Equation							
$\delta(1)_{11}$	0.978	0.989	0.997	0.987	1.002	1.002	0.995
	[163.311]*	[427.678]*	[334.660]*	[235.169]*	[374.460]*	[513.038]*	[630.399]*
$\delta(1)_{12}$	0.029	0.003	0.003	0.001	-0.003	-0.006	-0.000
	[3.881]*	[2.956]	[1.308]	[0.656]	[-0.692]	[-2.293]**	[-0.171]
μ_1	-0.215	0.041	0.010	0.010	0.005	-0.027	0.026
	[-3.773]*	[4.572]*	[0.667]	[0.962]	[0.453]	[-1.670]***	[2.198]**
$\delta(1)_{21}$	0.007	-0.008	-0.004	-0.012	0.003	0.004	-0.000
	[1.478]	[-17.307]*	[-0.944]	[-3.188]*	[1.140]	[2.051]**	[-0.396]
$\delta(1)_{22}$	0.992	1.004	1.002	1.002	0.989	0.992	0.990
	[168.618]*	[2654.274]*	[305.054]*	[666.706]*	[186.387]*	[310.205]*	[271.964]*
μ_2	0.062	0.026	0.025	0.001	0.024	-0.045	-0.009
	[1.405]	[9.547]*	[1.050]	[0.171]	[2.085]**	[-2.330]**	[-0.729]
Panel B. Variance Equation							
c_{11}	-0.032	0.018	0.013	0.018	-0.021	-0.018	-0.020
	[-11.970]*	[11.236]*	[6.674]*	[8.432]*	[-7.240]*	[-6.541]*	[-8.998]*
c_{21}	0.008	0.018	-0.007	0.017	-0.016	0.001	-0.011
	[3.102]*	[7.827]*	[-0.967]	[6.264]*	[-5.521]*	[0.254]	[-7.165]*
c_{22}	-0.000	-0.013	-0.017	-0.012	-0.011	-0.027	0.000
	[-0.004]	[-12.768]*	[-3.051]*	[-13.752]*	[-8.449]*	[-10.518]*	[0.000]
a_{11}	-0.264	0.462	-0.039	0.430	-0.134	-0.033	-0.003
	[-7.033]*	[10.305]*	[-1.361]	[9.788]*	[-1.506]	[-0.952]	[-0.104]
a_{12}	0.057	-0.143	0.113	-0.101	-0.463	0.769	0.708
	[1.849]***	[-5.496]*	[2.574]*	[-2.427]**	[-6.267]*	[15.780]*	[19.086]*
a_{21}	-0.759	-0.195	-0.685	-0.194	-0.184	-0.005	-0.157
	[-16.482]*	[-4.526]*	[-24.247]*	[-3.888]*	[-1.997]**	[-0.178]	[-5.451]*
a_{22}	0.008	0.405	0.034	0.435	0.296	0.434	0.527
	[0.231]	[13.862]*	[1.001]	[9.147]*	[3.502]*	[13.465]*	[17.842]*
b_{11}	0.269	0.961	0.269	0.913	0.709	0.871	0.827
	[4.485]*	[53.600]*	[7.260]*	[42.708]*	[14.498]*	[29.047]*	[28.381]*
b_{12}	-0.311	0.190	-0.373	0.131	-0.082	0.228	-0.221
	[-6.736]*	[11.709]*	[-6.427]*	[5.108]*	[-1.757]**	[4.327]*	[-8.933]*
b_{21}	0.377	-0.116	0.176	-0.025	0.154	-0.282	0.254
	[9.167]*	[-4.529]*	[3.831]*	[-0.820]	[2.894]*	[-7.305]*	[9.009]*
b_{22}	0.944	0.648	0.882	0.713	0.951	0.340	0.602
	[70.835]*	[21.834]*	[34.279]*	[18.659]*	[21.060]*	[7.437]*	[18.365]*

See Notes to Table 4.

Table 13. Summary of estimated results for the conditional mean and conditional variance equations between ETH and other cryptocurrencies

	ADA	BCH	BTC	EOS	LTC	XLM	XRP	
Panel A. Mean spillovers								
ETH	→	←	-	←	-	↔	-	1 bidirectional 3 unidirectional 3 no spillover
Panel B. Shock Transmission								
ETH	↔	↔	↔	↔	↔	→	↔	6 bidirectional 1 unidirectional
Panel C. Volatility Spillovers								
ETH	↔	↔	↔	→	↔	↔	↔	6 bidirectional 1 unidirectional

See Notes to Table 5.

Table 14. Estimated results of volatility spillover between LTC and other cryptocurrencies based on VAR-BEKK-GARCH model

	LTC-ADA	LTC-BHC	LTC-BTC	LTC-EOS	LTC-ETH	LTC-XLM	LTC-XRP
Panel A. Mean Equation							
$\delta(1)_{11}$	0.997 [1140.356]*	0.986 [316.774]*	0.997 [529.954]*	0.982 [195.517]*	1.002 [374.460]*	0.992 [344.348]*	0.977 [389.726]*
$\delta(1)_{12}$	0.009 [4.679]*	0.009 [2.430]**	0.004 [1.722]***	0.006 [1.633]***	-0.003 [-0.692]	0.004 [1.922]***	0.018 [6.356]*
μ_1	-0.046 [-4.905]*	0.036 [5.407]*	0.007 [0.698]	-0.003 [-0.275]	0.005 [0.453]	0.040 [2.469]**	0.113 [8.485]*
$\delta(1)_{21}$	0.002 [2.236]**	-0.011 [-4.136]*	-0.001 [-0.649]	-0.014 [-3.157]*	0.003 [1.140]	0.006 [1.707]***	0.004 [1.634]
$\delta(1)_{22}$	0.995 [546.103]*	1.007 [283.029]*	0.999 [275.031]*	1.004 [275.965]*	0.989 [186.387]*	0.995 [367.141]*	0.992 [283.346]*
μ_2	0.025 [2.867]*	0.039 [4.311]*	0.017 [1.248]	-0.000 [-0.037]	0.024 [2.085]**	-0.035 [-1.796]***	-0.030 [-1.939]***
Panel B. Variance Equation							
c_{11}	0.008 [4.032]*	-0.019 [-10.351]*	-0.017 [-16.763]*	0.020 [10.172]*	-0.021 [-7.240]*	0.024 [8.402]*	0.051 [25.432]*
c_{21}	0.031 [14.813]*	-0.019 [-9.647]*	-0.011 [-1.150]	0.019 [7.204]*	-0.016 [-5.521]*	0.015 [2.883]*	0.000 [0.589]
c_{22}	-0.000 [-0.001]	0.010 [9.222]*	-0.024 [-11.230]*	-0.011 [-7.568]*	-0.011 [-8.449]*	0.005 [0.304]	-0.000 [-0.000]
a_{11}	0.270 [7.594]*	0.536 [15.031]*	0.011 [0.392]	0.429 [11.534]*	-0.134 [-1.506]	0.067 [1.891]***	0.012 [0.364]
a_{12}	-0.160 [-4.583]*	-0.019 [-0.529]	0.019 [0.360]	-0.115 [-3.014]*	-0.463 [-6.267]*	0.714 [17.712]*	0.733 [20.004]*
a_{21}	0.669 [16.641]*	-0.322 [-7.445]*	-0.634 [-24.238]*	-0.257 [-8.949]*	-0.184 [-1.997]**	-0.144 [-4.468]*	-0.141 [-3.908]*
a_{22}	0.071 [2.016]**	0.284 [7.191]*	0.013 [0.392]	0.305 [8.019]*	0.296 [3.502]*	0.427 [14.675]*	0.501 [15.296]*
b_{11}	0.721 [28.359]*	0.888 [71.814]*	0.180 [3.857]*	0.949 [57.474]*	0.709 [14.498]*	-0.795 [-21.363]*	0.103 [0.443]
b_{12}	0.257 [8.333]*	0.074 [3.901]*	-0.474 [-7.695]*	0.176 [7.382]*	-0.082 [-1.757]**	0.287 [6.663]*	-0.123 [-3.417]*
b_{21}	-0.361 [-11.855]*	-0.000 [-0.016]	0.016 [0.202]	-0.085 [-4.745]*	0.154 [2.894]*	-0.268 [-8.930]*	0.125 [2.484]**
b_{22}	0.669 [14.762]*	0.798 [40.304]*	0.805 [13.680]*	0.707 [17.574]*	0.951 [21.060]*	-0.528 [-14.450*	0.626 [22.698]*

See Notes to Table 4.

Table 15. Summary of estimated results for the conditional mean and conditional variance equations between LTC and other cryptocurrencies

	ADA	BHC	BTC	EOS	ETH	XLM	XRP	
Panel A. Mean spillovers								
LTC	↔	↔	→	↔	-	↔	→	4 bidirectional 2 unidirectional 1 no spillover
Panel B. Shock Transmission								
LTC	↔	←	←	↔	↔	↔	↔	5 bidirectional 2 unidirectional
Panel C. Volatility Spillovers								
LTC	↔	→	→	↔	↔	↔	↔	5 bidirectional 2 unidirectional

See Notes to Table 5.

Table 16. Estimated results of volatility spillover between XLM and other cryptocurrencies based on VAR-BEKK-GARCH model

	XLM-ADA	XLM-BHC	XLM-BTC	XLM-EOS	XLM-ETH	XLM-LTC	XLM-XRP
Panel A. Mean Equation							
$\delta(1)_{11}$	1.007 [405.263]*	0.993 [210.456]*	1.001 [2247.466]*	0.983 [187.971]*	1.002 [513.038]*	0.992 [344.348]*	0.998 [217.918]*
$\delta(1)_{12}$	-0.012 [-2.805]*	0.002 [0.661]	-0.002 [-1.960]**	0.002 [0.784]	-0.006 [-2.293]**	0.004 [1.922]***	-0.004 [-0.760]
μ_1	-0.008 [-1.499]	0.040 [1.235]	-0.016 [-4.584]*	0.021 [1.820]**	-0.027 [-1.670]***	0.040 [2.469]**	-0.008 [-1.662]**
$\delta(1)_{21}$	0.004 [2.182]**	0.003 [0.725]	0.005 [2.855]*	-0.001 [-0.357]	0.004 [2.051]**	0.006 [1.707]***	-0.005 [-1.419]
$\delta(1)_{22}$	0.988 [251.935]*	0.996 [294.501]*	0.994 [395.314]*	0.996 [368.026]*	0.992 [310.205]*	0.995 [367.141]*	1.001 [175.586]*
μ_2	-0.013 [-2.531]**	-0.026 [-0.817]	-0.063 [-3.072]*	-0.007 [-0.662]	-0.045 [-2.330]**	-0.035 [-1.796]***	-0.012 [-2.624]*
Panel B. Variance Equation							
c_{11}	-0.028 [-12.430]*	0.022 [5.894]*	0..016 [11.554]*	-0.018 [-4.753]*	-0.018 [-6.541]*	0.024 [8.402]*	0.026 [8.044]*
c_{21}	-0.025 [-10.347]*	0.011 [1.791]**	0.013 [4.941]*	-0.001 [-0.197]	0.001 [0.254]	0.015 [2.883]*	0.011 [4.604]*
c_{22}	0.012 [12.249]*	0.019 [3.902]*	0.018 [13.622]*	0.026 [11.707]*	-0.027 [-10.518]*	0.005 [0.304]	0.013 [11.769]*
a_{11}	0.303 [5.849]*	0.000 [0.000]	0.427 [8.780]*	-0.005 [-0.128]	-0.033 [-0.952]	0.067 [1.891]***	0.281 [5.310]*
a_{12}	-0.264 [-5.363]*	0.674 [16.537]*	-0.246 [-3.811]*	0.768 [18.266]*	0.769 [15.780]*	0.714 [17.712]*	-0.311 [-6.216]*
a_{21}	0.099 [1.728]	-0.087 [-2.293]**	-0.042 [-1.341]	-0.025 [-0.708]	-0.005 [-0.178]	-0.144 [-4.468]*	-0.046 [-0.794]
a_{22}	0.672 [11.836]*	0.374 [11.053]*	0.541 [13.019]*	0.353 [8.829]*	0.434 [13.465]*	0.427 [14.675]*	0.799 [13.614]*
b_{11}	0.908 [35.058]*	0.790 [18.957]*	0.758 [22.779]*	0.869 [28.963]*	0.871 [29.047]*	-0.795 [-21.363]*	0.654 [7.207]*
b_{12}	0.109 [4.294]*	-0.196 [-5.759]*	0.066 [3.973]*	-0.054 [-1.020]	0.228 [4.327]*	0.287 [6.663]*	0.106 [1.898]**
b_{21}	-0.193 [-4.020]*	0.403 [8.566]*	0.059 [2.149]**	0.299 [6.866]*	-0.282 [-7.305]*	-0.268 [-8.930]*	0.223 [2.951]*
b_{22}	0.623 [13.368]*	0.497 [9.380]*	0.772 [30.694]*	0.367 [7.237]*	0.340 [7.437]*	-0.528 [-14.450*	0.712 [14.179]*

See Notes to Table 4.

Table 17. Summary of estimated results for the conditional mean and conditional variance equations between XLM and other cryptocurrencies

	ADA	BHC	BTC	EOS	ETH	LTC	XRP	
Panel A. Mean spillovers								
XLM	↔	-	↔	-	↔	↔	-	4 bidirectional 3 no spillover
Panel B. Shock Transmission								
XLM	→	↔	→	→	→	↔	→	2 bidirectional 5 unidirectional
Panel C. Volatility Spillovers								
XLM	↔	↔	↔	←	↔	↔	↔	6 bidirectional 1 unidirectional

See Notes to Table 5.

Table 18. Estimated results of volatility spillover between XRP and other cryptocurrencies based on VAR-BEKK-GARCH model

	XRP-ADA	XRP-BHC	XRP-BTC	XRP-EOS	XRP-ETH	XRP-LTC	XRP-XLM
Panel A. Mean Equation							
$\delta(1)_{11}$	1.006 [474.627]*	0.978 [216.290]*	1.003 [4703.876]*	0.999 [218.300]*	0.995 [630.399]*	0.977 [389.726]*	0.998 [217.918]*
$\delta(1)_{12}$	-0.017 [-3.282]*	0.012 [2.733]*	-0.005 [-6.558]*	-0.003 [-0.968]	-0.000 [-0.171]	0.018 [6.356]*	-0.004 [-0.760]
μ_1	-0.002 [-0.739]	0.131 [4.434]*	0.114 [12.144]*	-0.007 [-0.887]	0.026 [2.198]**	0.113 [8.485]*	-0.008 [-1.662]**
$\delta(1)_{21}$	0.003 [1.914]**	0.001 [0.308]	0.017 [10.055]*	0.011 [2.953]*	-0.000 [-0.396]	0.004 [1.634]	-0.005 [-1.419]
$\delta(1)_{22}$	0.988 [257.551]*	0.992 [258.268]*	0.992 [1188.880]*	0.987 [277.834]*	0.990 [271.964]*	0.992 [283.346]*	1.001 [175.586]*
μ_2	-0.007 [-2.017]**	-0.015 [-0.730]	-0.108 [-8.530]*	-0.030 [-3.632]*	-0.009 [-0.729]	-0.030 [-1.939]***	-0.012 [-2.624]*
Panel B. Variance Equation							
c_{11}	-0.023 [-12.245]*	-0.017 [-7.564]*	0.002 [9.201]*	-0.028 .[-11.028]*	-0.020 [-8.998]*	0.051 [25.432]*	0.026 [8.044]*
c_{21}	-0.019 [-8.572]*	-0.010 [-6.487]*	0.000 [0.529]	0.011 [7.795]*	-0.011 [-7.165]*	0.000 [0.589]	0.011 [4.604]*
c_{22}	-0.011 [-11.883]*	-0.000 [-0.000]	0.010 [13.615]*	-0.000 [-0.000]	0.000 [0.000]	-0.000 [-0.000]	0.013 [11.769]*
a_{11}	0.355 [9.816]*	0.084 [2.875]	0.450 [18.630]*	-0.195 [-5.234]*	-0.003 [-0.104]	0.012 [0.364]	0.281 [5.310]*
a_{12}	-0.208 [-5.152]*	0.597 [17.949]*	-0.002 [-0.757]	0.749 [22.283]*	0.708 [19.086]*	0.733 [20.004]*	-0.311 [-6.216]*
a_{21}	0.129 [3.267]*	-0.120 [-4.059]*	0.026 [4.795]*	0.012 [0.408]	-0.157 [-5.451]*	-0.141 [-3.908]*	-0.046 [-0.794]
a_{22}	0.825 [16.447]*	0.410 [14.718]*	0.490 [26.365]*	0.420 [15.397]*	0.527 [17.842]*	0.501 [15.296]*	0.799 [13.614]*
b_{11}	0.889 [51.801]*	0.891 [39.089]*	0.920 [133.675]*	0.791 [23.321]*	0.827 [28.381]*	0.103 [0.443]	0.654 [7.207]*
b_{12}	0.053 [2.472]**	-0.155 [-8.869]*	0.002 [3.301]*	0.130 [7.608]*	-0.221 [-8.933]*	-0.123 [-3.417]*	0.106 [1.898]**
b_{21}	-0.125 [-5.516]*	0.238 [6.733]*	-0.012 [-3.404]*	0.257 [9.774]*	0.254 [9.009]*	0.125 [2.484]**	0.223 [2.951]*
b_{22}	0.655 [22.533]*	0.674 [28.272]*	0.863 [81.933]*	0.544 [18.530]*	0.602 [18.365]*	0.626 [22.698]*	0.712 [14.179]*

See Notes to Table 4.

Table 19. Summary of estimated results for the conditional mean and conditional variance equations between XRP and other cryptocurrencies

	ADA	BHC	BTC	EOS	ETH	LTC	XLM	
Panel A. Mean spillovers								
XRP	↔	→	↔	←	-	→	-	2 bidirectional 3 unidirectional 2 no spillover
Panel B. Shock Transmission								
XRP	↔	↔	←	→	↔	↔	↔	5 bidirectional 2 unidirectional
Panel C. Volatility Spillovers								
XRP	↔	↔	↔	↔	↔	↔	↔	7 bidirectional

See Notes to Table 5.

6. Discussion and Conclusion

Through the application of MGARCH with the BEKK parameterization model for eight major cryptocurrencies, BTC, ETH, LTC, XRP, XLM, BCH, ADA and EOS, this paper empirically investigates mean and volatility transmission between pairs of cryptocurrencies using daily data covering the period from June 2018 to September 2021. The results of VAR-BEKK-GARCH model indicate evidence of bidirectional and unidirectional shock and volatility connectedness among most cryptocurrency pairs. The results of interdependencies in the crypto market are in line with the findings of Fry and Cheah (2016), Corbet et al. (2018), Ciaian and Rajcaniova (2018), and Katsiampa (2018a, b). This interconnectedness provides strong evidence supporting the progress of cryptocurrency market integration and moreover supports previous studies' findings on interdependencies in the crypto market.

It should be noticed that there is no evidence of volatility spillover effects only for the pair of BCH- BTC. However, there is a unidirectional shock transmission effect from BCH to BTC, highlighting that past news about shocks in BCH affects the current conditional volatility of BTC. Although BTC plays a truly important role and generates strong volatility shocks for other cryptocurrencies, it does not completely dominate the market. This result perfectly aligns with the existing literature in which Yi et al. (2018) claimed that BTC is not the clear leader in terms of volatility connectedness, and Fasanya et al. (2021) concluded that BTC exerts more volatility influence compared to other cryptocurrencies, although not significantly higher.

Furthermore, most unidirectional volatility spillover effects are observed from LTC to BCH and BTC, indicating that LTC has the dominant transmitting role. On the other hand, concerning volatility receivers from others, XLM is the only one acting as a receiver. These unexpected results are similar to Corbet et al. (2018), who found that cryptocurrencies are highly interconnected, while Bitcoin has no clear leading role for volatility spillovers. Comparing our results regarding shock transmission, the 2015-2018 dataset derived from the study of Moratis (2021) suggested that XRP is the only single net receiver of shocks, while BTC remains a net transmitter. According to our results, while BTC is still a net transmitter, XLM is the new net receiver. XRP remained among the top three in total crypto market capitalization between the years 2015-2018 with less volatility, however, after 2018, it lost its position with a considerable downside movement against BTC.

These findings have implications for both investors, portfolio managers and also for market regulators. Market spillovers are vital while designing portfolios and investors can diversify the risks by including cryptocurrencies. They can also pay attention to the new cryptocurrencies.

On the other hand, market regulators should be aware that the cryptocurrencies are connected, and thus, should consider spillover effects in their policymaking and implementations. Assessment of the effects of connectedness among cryptocurrencies can be used by policy makers to identify the transmitter/recipient in the financial system and thus, support efforts to stabilize the system. The fact that the empirical results point to the evidence of volatility spillovers in cryptocurrency market motivates us to examine the implications of such results on portfolio designs through the optimal portfolio weights and effective hedging ratios of cryptocurrency holdings in our further studies.

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