www.cya.unam.mx/index.php/cya

Contaduría y Administración 68 (1), 2023, 1-22

Volatility spillover between the cryptocurrency and financial markets and commodities

Spillover de volatilidad entre el mercado de las criptomonedas, los mercados financieros y commodities

Erik Mauricio Muñoz Henríquez[*1], Francisco Andrés Gálvez Gamboa[2]

[1] Universidad de Talca, Chile
[2] Universidad Católica del Maule, Chile

Received June 28, 2021; accepted September 27, 2022
Available online September 29, 2023

Abstract

The aim of this paper is to analyze the spillover effect between the cryptocurrency market and the financial markets, using realized volatility indices of the ten cryptocurrencies with the largest market capitalization and the implied volatility of Gold (GVZ) and Oil (OVX) prices, and the North American (VIX) and European (VSTOXX) financial market through the Spillover Index based on a Vector Autoregressive (VAR). The results indicate that Ethereum is the largest volatility transmitter followed by Cardamo, while ChainLink and BinanceCoin are the largest receivers. We demonstrate with implied volatility that contribution of volatility spillover from financial markets does not exceed 3%, even lower results are evidenced from both commodities. Impulse-response analysis shows the major effect of the VIX on cryptocurrencies, along with a negative response to a shock in commodities indices.

JEL Code: C58, G10, G15, G17
Keywords: cryptocurrency; spillover effect; volatility

[*] Corresponding author.
E-mail address: emunozhenriquez@outlook.com (E. M. Muñoz Henríquez).
Peer Review under the responsibility of Universidad Nacional Autónoma de México.

http://dx.doi.org/10.22201/fca.24488410e.2023.3396

Resumen

El objetivo de este trabajo es analizar el efecto spillover entre el mercado de las criptomonedas, los mercados financieros y commodities, utilizando índices de volatilidad realizada de las diez criptomonedas con mayor capitalización de mercado y la volatilidad implícita de las cotizaciones del Oro (GVZ) y el Petróleo (OVX), y el mercado financiero norteamericano (VIX) y europeo (VSTOXX) a través del Spillover Index basado en un Vector Autorregresivo (VAR). Los resultados indican que Ethereum es el mayor transmisor de volatilidad, seguido por Cardamo, mientras que los mayores receptores de volatilidad son ChainLink y BinanceCoin. Además, demostramos a través de la utilización de la volatilidad implícita que la contribución de los mercados financieros al spillover no excede el 3%, incluso resultados menores se evidencian con ambos commodities. El análisis de impulso-respuesta muestra el mayor efecto sobre las criptomonedas proviene del VIX, junto con una respuesta negativa ante un shock en el OVX y GVZ.

Código JEL: C58, G10, G15, G17
Palabras clave: : criptomoneda; efecto spillover; volatility

Introduction

Since the introduction of the first cryptocurrency—Bitcoin in 2009 by Satoshi Nakamoto—the cryptocurrency market has gained great popularity in recent years, generating a large volume of transactions in its trading. Figure 1 shows the evolution from 2015 to 2021 of the capitalization of all cryptocurrencies traded in the market, exceeding USD 2.2 trillion.

In this context—the circulation of this new financial asset and the integration of markets—any knowledge that can be developed about these assets is highly relevant, both for investors and for risk management strategies (Okorie & Lin, 2020; Symitsi & Chalvatzis, 2018).

Figure 1. Total Market Capitalization in USD of the Cryptocurrency Market
Source: TradingView (2021)

http://dx.doi.org/10.22201/fca.24488410e.2023.3396

Recent studies have focused on the characteristics of cryptocurrencies, mainly Bitcoin, classifying it as a financial asset, a commodity, or a currency (Baur, Hong, & Lee, 2015; Kristjanpoller & Bouri, 2019; Gronwald, 2019). Moreover, lines of research studying the determinants of the price of this cryptocurrency have also been developed (Dyhrberg, 2016b). In recent years, the financial literature has considered it useful to analyze cryptocurrencies as an additional element in portfolio optimization and their hedging or risk minimization capacity (Okorie & Lin, 2020; Dwita Mariana, Ekaputra, & Husodo, 2020; Dyhrberg, 2016).

An important part of the literature has focused on the study of the spillover of the cryptocurrency market, which is a commonly used methodology for analyzing the connection between markets and financial assets (Corbet et al., 2018; Balli et al., 2020). Studies that have examined the spillover index to date have taken daily returns of cryptocurrencies as their basis (Symitsi & Chalvatzis, 2018; Ji, Bouri, Lau, & Roubaud, 2019; Fousekis & Tzaferi, 2021; Akyildirim, Corbet, Lucey, Sensoy, & Yarovaya, 2020).

This paper proposes the use of volatility in the analysis of the cryptocurrency market, a measure of great interest for investors and a quantitative indicator of risk, which will extend the literature on this topic. Furthermore, this work contributes to the study of the spillover index by using the volatility of the 10 cryptocurrencies with the largest market capitalization since it mainly focuses on Bitcoin. In addition to incorporating the analysis of the implied volatility of the North American (VIX), European (VSTOXX), Oil (OVX), and Gold (GVZ) stock exchanges, this paper shows a differentiated analysis of shocks between the markets and commodities with cryptocurrencies through the impulse response function.

The results differ from those commonly found in the literature, showing that Ethereum is the largest volatility transmitter, followed by Cardano and Litecoin. Moreover, the implied volatility of VIX and VSTOXX contribute to the volatility of cryptocurrencies in ranges below 3%. Even results below 1% are evident with OVX and GVZ, implying a disconnection with these markets.

This paper is structured as follows: Section 2 presents the literature review; Section 3 presents the methodological framework; Section 4 presents the data and some preliminary statistics; Section 5 presents the results; and Section 6 offers the main conclusions and implications.

Review of the literature

The recent popularity of the cryptocurrency market and its large volume of transactions has increased interest in understanding the behavior of these assets and their relation to financial markets. Authors such as Fang et al. (2022) show the exponential growth in the number of publications regarding the crypto market from 2013 to 2021, showing that 85% is concentrated since 2018. It coincides with the increase in the market capitalization of cryptocurrencies (Figure 1), proving to be a new area of research in financial trading.

Consequently, it is possible to identify various methodologies in the literature used to study the volatility of cryptocurrencies and their relation to other markets. They mainly focus on two approaches: 1) the Generalized Autoregressive Conditional Heteroscedasticity (GARCH) model and 2) Vector Autoregressions (VARs) in their different variants.

In the first approach, GARCH models are commonly used to study the relation between market and financial assets. For example, using the Dynamic Conditional Correlations (DCC) approach, Dwita Mariana et al. (2020) analyzed the two cryptocurrencies with the largest market capitalization, Bitcoin and Ethereum. They analyzed the cryptocurrencies, along with the S&P500 and Gold, before and during the COVID-19 pandemic, identifying a negative correlation with S&P500 returns during the pandemic and concluding that Ethereum is a better safe-haven than Bitcoin.

Additionally, using a multivariate iGARCH-DCC model and the 4 main cryptocurrencies (Bitcoin, Ethereum, Ripple, and Litecoin), Kumar and Anandarao (2019) identified a significant spillover from Bitcoin to Ethereum and Litecoin. Moreover, a wavelet analysis confirms Bitcoin's predominant effect over other cryptocurrencies, suggesting the possibility of including cryptocurrencies in investors' portfolio diversification in times of low market volatility.

Conversely, using a VAR-GARCH model, Symitsi and Chalvatzis (2018) study the spillover effect between the Bitcoin, S&P Global Clean Energy Index, and companies related to energy and technology, identifying a spillover of returns in the event of a shock in energy and technology companies on Bitcoin. Following this line, Umar et al. (2021) analyzed the daily returns of 12 technology sectors in developed and developing economies and Bitcoin, demonstrating the existence of significant interconnections in this sector worldwide. They also found that the contribution of the cryptocurrency market is negligible, showing less exposure to systematic risk, which reduces exposure to possible warnings from regulatory entities.

In the second approach, VAR models can be found with different innovations, such as the one developed by Diebold and Yilmaz (2012), based on the variance decomposition of the forecast error of an autoregressive vector (VAR). For example, Gillaizeau et al. (2019) analyzed the spillover between Bitcoin and different currencies by calculating the exchange rates, finding that Bitcoin-USD possesses a net predictive power and Bitcoin-EURO is a net receiver. In addition, the authors demonstrated that in periods of high volatility, Bitcoin shows great dynamic inefficiency, so that it is necessary for investors to have very definite information to predict the expected return.

Separately, Corbet et al. (2018) analyzed the relation of the three major cryptocurrencies (Bitcoin, Ripple, and Litecoin) in the market during 2017 with other financial assets such as MSC GSCI Total Returns Index, US$ Broad Exchange Rate, SP500 Index, COMEX gold closing prices, VIX, and the Markit ITTR110 index. Their methodology leads them to conclude that there is a strong connection between cryptocurrencies and a relative disconnection from the main financial assets.

Similarly, Balli et al. (2020) studied the six cryptocurrencies with the largest capitalization (Bitcoin, Ripple, Stellar, Litecoin, Monero, and Dash) together with the Economic Policy Uncertainty Index (EPU), VIX, OVX, and GVZ, demonstrating that cryptocurrencies are negatively correlated with economic uncertainty even when using cryptocurrencies as a portfolio diversification tool to minimize risk. Similar research has been carried out by Ghorbel, Loukil, and Bahloul (2022),

Recent studies, such as Moratis (2021), quantified the spillover effect in the 30 cryptocurrencies with the largest market capitalization using a Bayesian VAR. Bitcoin was identified as the cryptocurrency that dominates spillover, and some cryptocurrencies appeared to be immune to spillover transmitters.

Similarly, there are other methodologies to study the behavior of cryptocurrencies, such as the VAR-MGARCH-GJR-BEKK technique used by Okorie and Lin (2020). They identified the existence of bidirectional and unidirectional volatility spillover from crude oil to cryptocurrencies and vice versa by using the 5 cryptocurrencies with the smallest and largest capitalization and crude oil. Furthermore, they found that risk can be reduced by incorporating the commodity into their portfolios.

An important feature contained in the literature is the trade-off that authors must make between the period under study (Ji et al., 2019; Brauneis y Mestel, 2018; Fousekis & Tzaferi, 2021) and the number of cryptocurrencies included in the analysis (Zięba, Kokoszczyński, & Śledziewska, 2019). Therefore, this paper provides a longer analysis for the period under study of the behavior of cryptocurrencies with higher capitalization and implied volatilities of different markets.

Methodology

The methodology proposed by Diebold and Yilmaz (2012), based on the decompositions of the forecast error variance in a generalized vector autoregressive framework, is used to quantify the spillover effect in the cryptocurrency market and other financial indicators. The use of this method is based on the fact that markets are connected to each other, regardless of the existence of shocks that affect their correlations (Forbes & Rigobon, 2002), so the use of conditional models can generate biases in the estimation, as would be the case of the DCC-GARCH models (Elsayed, Gozgor, & Yarovaya, 2022).

Therefore, the VAR model can be defined as:

$$y_t = \sum_{i=1}^{p} \Phi\, y_{t-1} + \varepsilon_t \tag{1}$$

Where y_t is the vector of size M containing all volatilities in period t, and $\varepsilon_t \sim N(0, \Sigma)$ is a vector of disturbances. The variance decomposition of the generalized H-step forward forecast error is defined by:

$$\theta_{ij}^{g}(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} \left(e_i' A_h \Sigma e_j\right)^2}{\sum_{h=0}^{H-1} \left(e_i' A_h \Sigma A_h' e_i\right)^2} \tag{2}$$

Where $H = 1,2,\ldots$, and $i, j = 1,2, \ldots, M$. Σ is the variance-covariance matrix of the disturbance vector ε_t, σ_{jj} is the standard deviation of the error term for the *j*-th equation, A_h is the coefficient matrix of the lagged disturbance vector h in the infinite moving mean representation of the VAR model, and e_i is the selection vector, with one as the i-th element and zeros otherwise. The sum of the elements in each row of the variance decomposition table does not equal one $\sum_{j=1}^{M} \theta_{ij}^{g}(H) \neq 1$, since the shocks are not necessarily orthogonal. The estimates should be normalized to compare the directional spillover effects by individual pairs

$$\tilde{\theta}_{ij}^{g}(H) = \frac{\theta_{ij}^{g}(H)}{\sum_{j=1}^{M} \theta_{ij}^{g}(H)} \tag{3}$$

By construction $\sum_{j=1}^{M} \tilde{\theta}_{ij}^{g}(H) = 1$ and $\sum_{i,j=1}^{M} \tilde{\theta}_{ij}^{g}(H) = M$. To simplify the notation, $S_{i\leftarrow j}^{H}$ will be used instead of $\tilde{\theta}_{ij}^{g}(H)$ to describe the direction of the spillover effect in the different series.

The directional volatility spillover received by market i from all other markets j can be defined as follows:

$$S_{i\leftarrow \circ}^{H} = \frac{\sum_{\substack{j=1 \\ j\neq i}}^{M} \tilde{\theta}_{ij}^{g}(H)}{M} \tag{4}$$

At the same time, the contribution of market j to all other markets i is given by:

$$S_{\circ\leftarrow j}^{H} = \frac{\sum_{\substack{i=1 \\ i\neq j}}^{M} \tilde{\theta}_{ji}^{g}(H)}{M} \tag{5}$$

The net volatility spillover from market i to all other markets j corresponds to the difference between the directional spillover and can be calculated as follows

$$S_i^H = S_{\circ\leftarrow i}^H - S_{i\leftarrow\circ}^H \tag{6}$$

This measurement makes it possible to calculate how much market i contributes to the volatility of other markets or assets, as "net transmitters" ($S_i^H > 0$) and "net receivers" ($S_i^H < 0$) can be identified.

Finally, the total spillover ratio can be constructed as:

$$S^H = \frac{\sum_{\substack{i,j=1 \\ i\neq j}}^{M} \tilde{\theta}_{ji}^{g}(H)}{M} \tag{7}$$

The total spillover is the ratio of the sum of the off-diagonal elements of $\tilde{\theta}_{ij}^{g}(H)$ and the sum of all other elements.

In order to have a better understanding of the spillover table resulting from the implemented methodology, Table 1 provides a clear example of the aggregate and disaggregated spillover results, where $\boldsymbol{y_i}$ represents each market or asset used. The internal $\boldsymbol{d_{ij}}$ elements are the pairwise directional spillover from $\boldsymbol{y_j}$ to $\boldsymbol{y_i}$. They represent the contribution of a shock in $\boldsymbol{y_j}$ on the variance of the h-step ahead forecast error in $\boldsymbol{y_i}$.

The "From" column corresponds to the total directional spillover from $\boldsymbol{y_j}$ to others, and the "To" row is the total directional spillover from y_j to others.

Table 1
Spillover table

	y_1	y_2	$\cdots$	y_M	From
y_1	d_{11}	d_{12}	$\cdots$	d_{1M}	$\sum_{j=1}^{M} d_{1j}$; $j \neq 1$
y_2	d_{21}	d_{22}	$\cdots$	d_{2M}	$\sum_{j=1}^{M} d_{2j}$; $j \neq 2$
$\vdots$	$\vdots$	$\vdots$	$\cdots$	$\vdots$	$\vdots$
y_M	d_{1M}	d_{2M}	$\cdots$	d_{MM}	$\sum_{j=1}^{M} d_{Mj}$; $j \neq M$
To	$\sum_{\substack{i=1 \\ i\neq 1}}^{M} d_{i1}$	$\sum_{\substack{i=1 \\ i\neq 2}}^{M} d_{i2}$	$\cdots$	$\sum_{\substack{i=1 \\ i\neq M}}^{M} d_{iM}$	$\frac{1}{M}\sum_{i,j=1}^{M} d_{ij}$; $i \neq j$

Source: Diebold and Yılmaz (2015)

For analysis purposes, it is necessary to identify the net directional spillover (identification of transmitters and receivers) and the total net directional spillover, presented in Ec.(6) and , Ec.(7) respectively.

Data

Volatility is one of the most commonly used measures of risk or uncertainty in markets. Following Diebold and Yılmaz (2014) and Demirer *et al.* (2018), this study uses realized volatility (RV) based on a daily range, implementing the methodology developed by Garman and Klass (1980)

$$\hat{\sigma}_{it}^2 = 0.511(H_{it} - L_{it})^2 - 0.019[(C_{it} - O_{it})(H_{it} + L_{it} - 2O_{it}) - 2(H_{it} - O_{it})(L_{it} - O_{it})] - 0.383(C_{it} - O_{it})^2 \quad (8)$$

Where H_{it}, L_{it}, O_{it}, and C_{it} correspond to the highest, lowest, opening, and closing price, respectively, for cryptocurrency i in period t. One of the characteristics of this volatility measure is that under certain assumptions, it converges in probability to true volatility integrated with a standard normal distribution (Barndorff-Nielsen & Shephard, 2002).

Following authors such as Kumar and Anandarao (2019), Balli *et al.* (2020), and Ghorbel *et al.* (2022), this study focuses on the group of cryptocurrencies with the largest market capitalization. Specifically, the 10 largest cryptocurrencies[1] in terms of market capitalization as of April 22, 2021, are analyzed. Nonetheless, the sample of cryptocurrencies is limited to those with data from January 2018. Table 2 details the cryptocurrencies analyzed and their percentage of market capitalization as of 04/17/2021, representing more than 75% of the total cryptocurrencies traded in the market.

In addition, four Implied Volatility[2] (IV) indices are included: CBOE volatility index based on S&P500 index options (VIX), EURO STOXX 50 volatility index (VSTOXX) based on EURO STOXX 50 option prices, CBOE Crude Oil EFT volatility index (OVX), and CBOE Gold EFT volatility index (GVZ). The first two measures correspond to the US and European financial market risks. The next two implied volatilities are measures of commodity risk, both of which are generally used to hedge portfolio risk.

Table 2
Description of the 10 cryptocurrencies under analysis

Cryptocurrency	Abbreviation	Cryptocurrency
Bitcoin	BTC	51.64%
Ethereum	ETH	12.33%
BinanceCoin	BNC	0.24%
Tether	USDT	2.20%
XRP – Ripple	XRP	3.24%
Cardano	ADA	2.01%
DogeCoin	DOGE	1.71%

[1]Data from finance.yahoo.com
[2]Data from finance.yahoo.com, except VSTOOX which was obtained from wsj.com

http://dx.doi.org/10.22201/fca.24488410e.2023.3396

Litecoin	LTC	0.81%
ChainLink	LINK	0.80%
Stellar	XLM	0.66%

Source: created by the authors based on data obtained from coinmarketcap.com as of 04/17/2021

Figure 2 shows the volatilities of each cryptocurrency during 2018 and 2020, it being possible to identify high volatilities in most cryptocurrencies, particularly in two periods. The first is at the beginning of 2018, when there was a generalized drop in the price that these new assets traded at, after a great boom during 2017. This bearish trend continues throughout 2018. The second can be observed during March 2020, when investors liquidated safe-haven assets in search of cash after the fall of all markets due to Covid-19. This was the case with cryptocurrencies, bonds, and gold, and Figure 3 shows this volatility peak.

In accordance with the above, the volatility indexes of the US and European markets are at their highest in March 2020, with the generalized fall of the international stock markets due to the uncertainty caused by the global health crisis. The same results can be seen in the oil market, although it had a second shock during April 2020, labeled a "black day" for this commodity, with the West Texas International (WTI) trading with negative values.

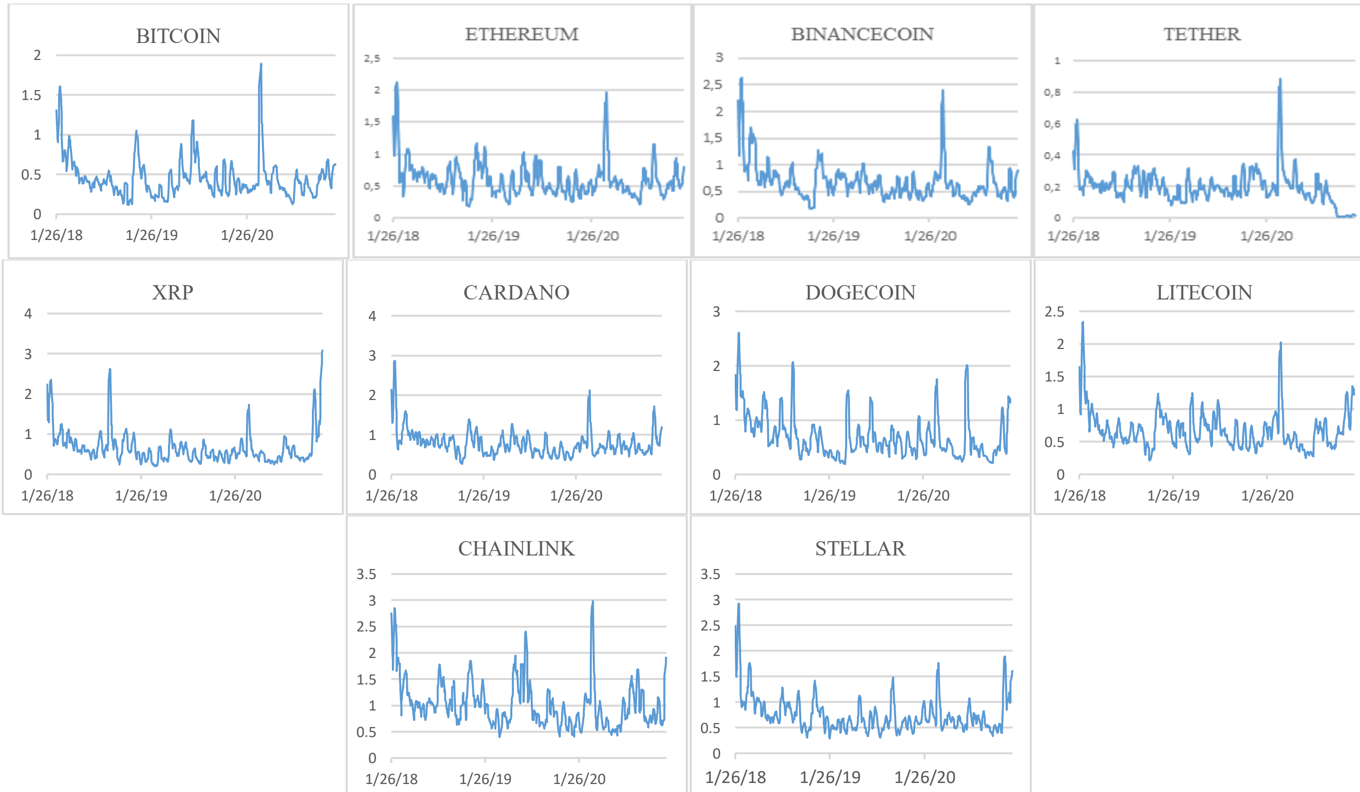

Figure 2. Realized Volatility of Cryptocurrencies
Source: created by the authors

http://dx.doi.org/10.22201/fca.24488410e.2023.3396

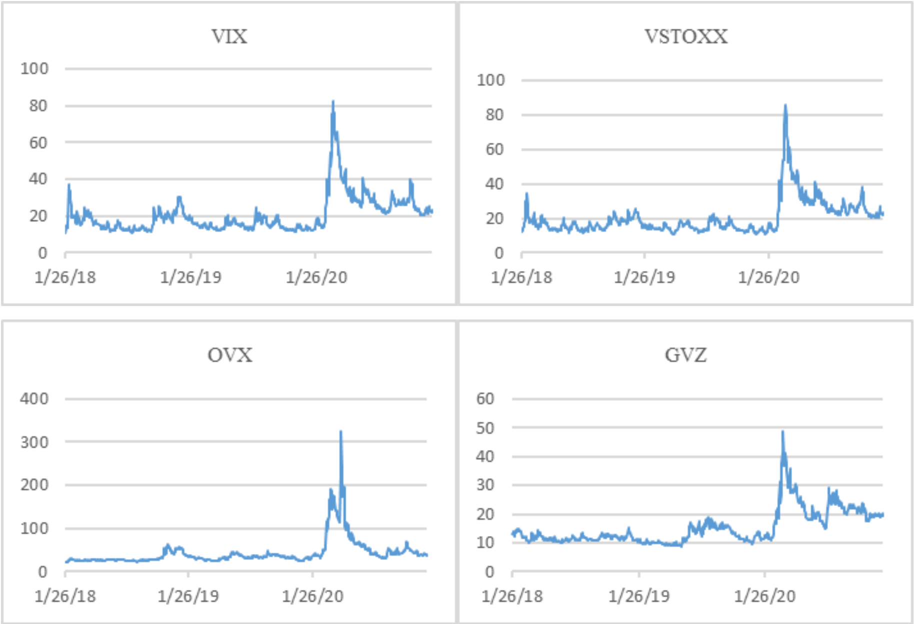

Figure 3. Implied volatilities of markets and commodities
Source: created by the authors

Table 3 shows the descriptive statistics of realized volatility (RV) and implied volatility (IV) for each cryptocurrency and stock market. The mean for cryptocurrency volatility varies between 0.20 (USDT) and 1.03 (LINK). In turn, the standard deviation is homogeneous for most cryptocurrencies, except for USDT, with a measure of 0.11. In the case of IVs, both OVX and GVZ present a lower and higher mean and standard deviation, respectively, showing great variability in both volatilities.

Conversely, all volatility indices have positive skewness and show a leptokurtic distribution. This is complemented by the Jarque-Bera test, which rejects the normality distribution of the observation. The Phillips-Perron test shows that all volatilities remain stationary at the 0.05 significance level.

Table 3
Descriptive statistics of volatilities

	Mean	SD	Min	Max	Skewness	Kurtosis	Jarque-Bera	Box-Pierce	Phillips-Perron
BTC	0.46	0.26	0.12	1.89	2.26	7.19	0.00	0.00	0.010
ETH	0.61	0.28	0.19	2.13	2.20	7.80	0.00	0.00	0.010
BNC	0.69	0.36	0.17	2.64	2.38	7.91	0.00	0.00	0.010
USDT	0.20	0.11	0.01	0.88	2.03	9.77	0.00	0.00	0.010
XRP	0.66	0.41	0.21	3.08	2.65	8.86	0.00	0.00	0.010
ADA	0.79	0.33	0.27	2.86	2.46	10.25	0.00	0.00	0.010
DOGE	0.70	0.41	0.20	2.61	1.68	3.35	0.00	0.00	0.010
LTC	0.68	0.30	0.21	2.34	2.07	7.09	0.00	0.00	0.010
LINK	1.03	0.45	0.40	2.98	1.57	3.34	0.00	0.00	0.010
XLM	0.76	0.37	0.29	2.92	2.39	8.53	0.00	0.00	0.010
VIX	20.58	10.05	10.85	82.69	2.54	8.88	0.00	0.00	0.024
VSTOXX	20.34	10.13	10.84	85.62	2.78	10.66	0.00	0.00	0.024
OVX	43.16	31.19	22.23	325.15	3.97	19.64	0.00	0.00	0.014
GVZ	15.29	6.05	8.88	48.98	1.79	4.06	0.00	0.00	0.045

Note: The Jarque-Bera and Box-Pierce test shows the p-values with 10 lags.
Source: created by the authors

Table 4 shows the correlations between the group of cryptocurrencies and the four implied volatilities. It is possible to identify a high level of correlation between cryptocurrencies, with values close to 0.85 in some cases. On the other hand, when analyzing the correlation of the implied volatilities of the North American and European markets, the degree of correlation is lower than between cryptocurrencies, with values ranging from 0.032 (DogeCoin - VIX) to 0.32 (Bitcoin - VSTOXX). In the case of implied commodity volatility, DogeCoin shows negative correlations with gold (-0.042) and oil (-0.074).

Table 4
Correlation of volatilities

	BTC	ETH	BNC	USDT	XRP	ADA	DOGE	LTC	LINK	XLM	VIX	VSTOXX	OVX	GVZ
BTC	1.000	0.855	0.774	0.655	0.586	0.765	0.576	0.839	0.749	0.679	0.318	0.321	0.202	0.249
ETH	0.855	1.000	0.858	0.682	0.704	0.872	0.577	0.880	0.772	0.775	0.285	0.281	0.138	0.190
BNC	0.774	0.858	1.000	0.589	0.558	0.802	0.553	0.796	0.730	0.741	0.245	0.233	0.079	0.097
USDT	0.655	0.682	0.589	1.000	0.380	0.532	0.426	0.521	0.511	0.451	0.293	0.318	0.247	0.170
XRP	0.586	0.704	0.558	0.380	1.000	0.727	0.540	0.712	0.603	0.799	0.072	0.074	-0.037	0.061
ADA	0.765	0.872	0.802	0.532	0.727	1.000	0.667	0.817	0.698	0.887	0.207	0.203	0.033	0.081

DOGE	0.576	0.577	0.553	0.426	0.540	0.667	1.000	0.609	0.568	0.680	0.032	0.041	-0.074	-0.042
LTC	0.839	0.880	0.796	0.521	0.712	0.817	0.609	1.000	0.729	0.760	0.209	0.203	0.040	0.125
LINK	0.749	0.772	0.730	0.511	0.603	0.698	0.568	0.729	1.000	0.657	0.152	0.148	0.000	0.081
XLM	0.679	0.775	0.741	0.451	0.799	0.887	0.680	0.760	0.657	1.000	0.096	0.090	-0.029	0.026
VIX	0.318	0.285	0.245	0.293	0.072	0.207	0.032	0.209	0.152	0.096	1.000	0.976	0.785	0.853
VSTOXX	0.321	0.281	0.233	0.318	0.074	0.203	0.041	0.203	0.148	0.090	0.976	1.000	0.790	0.863
OVX	0.202	0.138	0.079	0.247	-0.037	0.033	-0.074	0.040	0.000	-0.029	0.785	0.790	1.000	0.735
GVZ	0.249	0.190	0.097	0.170	0.061	0.081	-0.042	0.125	0.081	0.026	0.853	0.863	0.735	1.000

Source: created by the authors

Results

Total spillover analysis

To calculate the spillover index of realized volatility and implied volatility from January 26, 2018, to December 31, 2020, a 200-day moving window and the 10-step predictive horizon were used in the variance decomposition. Figure 4 shows the total system spillover where fluctuations between approximately 60% and 86% are identified

Figure 4. Total Spillover Index
Source: created by the authors

During mid-2018 and early 2020, a high level of connectivity was evident in the cryptocurrency market, which ranged between 60% and 75%. This is mainly explained by the volatility experienced by the cryptocurrency market since mid-2017, which has been driven by Bitcoin (Gandal et al., 2018; Antonakakis et al., 2019).

The cryptocurrency market suffered large contractions, from accumulating its highest values during 2017 to falling drastically in the first months of 2018. It presented high volatility throughout the year (see

Figure 2), consistent with the high spillover index at the beginning of Figure 4.

Subsequently, the spillover rate started to grow, intensifying the market connection by staying below 70%. This changed when all markets and assets were affected by the Covid-19 pandemic in early 2020, with high volatility, which, in turn, implied greater connectivity between the cryptocurrencies and markets under analysis, reaching levels close to 86%.

Spillover index analysis

Volatility spillover estimates for the 10 cryptocurrencies and the 4 indices are presented in Table 5 using a VAR model of order 1 (selection is based on the Schwarz Information Criterion) with a 10-step forward prediction horizon for variance decomposition. The 2018-2020 period under analysis shows a total spillover ratio (S^{H}) of 70.87%, demonstrating a highly integrated market.

The cryptocurrency with the greatest influence in its contribution to the volatility of other markets is Ethereum ($\mathrm{S}^{\mathrm{H}}_{\circ\leftarrow \mathrm{ETH}} = 100.35\%$), followed by Cardano ($\mathrm{S}^{\mathrm{H}}_{\circ\leftarrow \mathrm{ADA}} = 95.14\%$), Litecoin ($\mathrm{S}^{\mathrm{H}}_{\circ\leftarrow \mathrm{LTC}} = 94.54\%$), Stellar ($\mathrm{S}^{\mathrm{H}}_{\circ\leftarrow \mathrm{XLM}} = 91.97\%$), and Bitcoin ($\mathrm{S}^{\mathrm{H}}_{\circ\leftarrow \mathrm{BTC}} = 89.93\%$).

When analyzing the off-diagonal elements representing pairwise directional spillovers, the largest is Stellar to Cardano (13.40%), the second is Bitcoin to Tether (13.11%), and the third is Cardano to Stella (13.02%). On the other hand, the implied volatility that most influences the volatility of cryptocurrencies is VIX to Bitcoin ($S^{\mathrm{H}}_{\mathrm{BTC}\leftarrow \mathrm{VIX}} = 2.14\%$) and VSTOXX to Tether ($S^{\mathrm{H}}_{\mathrm{USDT}\leftarrow \mathrm{VSTOXX}} = 2.61\%$). Implied volatility associated with oil (OVX) and gold (GVZ) contributes less than 1% to the cryptocurrency market.

The last column of Table 5 shows the total net directional spillover ($\mathrm{S}^{\mathrm{H}}_{\mathrm{i}}$) where positive (negative) values corresponding to realized or implied volatilities are volatility spillover transmitters (receivers), (i.e., if $\mathrm{S}^{\mathrm{H}}_{\mathrm{i}} > 0$ it is a net contributor or $\mathrm{S}^{\mathrm{H}}_{\mathrm{i}} < 0$) it is a net receiver). Ethereum is the most important volatility transmitter, followed by Cardano and Litecoin. These findings align with those of Yi et al. (2018), where Bitcoin is not the cryptocurrency that dominates the market despite having the largest market capitalization.

Table 5
Spillover Index

	BTC	ETH	BNC	USDT	XRP	ADA	DOGE	LTC	LINK	XLM	VIX	VSTOXX	OVX	GVZ	$S^H_{i\leftarrow\circ}$	S^H_i
BTC	18.19	12.45	9.07	8.88	6.39	9.73	4.02	11.73	7.54	7.63	2.14	1.92	0.12	0.19	81.81	7.92
ETH	11.73	15.84	9.77	8.02	7.51	11.75	4.43	11.72	6.88	9.64	1.37	1.05	0.15	0.14	84.16	16.19
BNC	9.76	11.79	17.97	7.14	5.89	10.62	4.83	11.11	7.75	10.34	1.41	1.11	0.27	0.01	82.03	-6.38
USDT	13.11	12.26	9.06	22.41	6.09	8.19	3.32	8.67	6.33	6.45	1.23	2.61	0.17	0.12	77.59	-15.49
XRP	6.81	9.39	5.54	4.83	26.49	10.27	7.82	9.25	5.85	12.56	0.54	0.44	0.15	0.06	73.51	-4.01
ADA	9.07	11.81	8.48	5.85	9.12	17.33	6.14	10.57	6.03	13.40	1.12	0.92	0.11	0.05	82.67	12.48
DOGE	7.19	6.32	6.05	4.53	6.80	8.98	35.30	8.58	4.66	9.32	0.94	0.97	0.34	0.02	64.70	-13.96
LTC	11.71	12.26	9.05	7.38	6.86	10.60	5.88	17.75	6.52	9.53	1.12	0.87	0.42	0.06	82.25	12.29
LINK	9.20	10.15	8.44	5.48	7.78	8.68	5.67	9.19	22.40	9.33	1.66	1.33	0.70	0.01	77.60	-17.28
XLM	7.25	9.85	8.11	5.08	12.55	13.02	7.90	9.17	6.11	20.05	0.53	0.30	0.04	0.04	79.95	11.76
VIX	1.24	1.37	0.95	1.28	0.14	1.46	0.25	1.76	0.89	1.47	45.10	31.19	1.58	11.32	54.90	32.95
VSTOXX	1.40	1.34	0.78	1.78	0.18	1.41	0.37	1.63	0.81	1.39	37.68	38.58	1.14	11.51	61.42	17.92
OVX	0.48	0.67	0.24	1.24	0.02	0.08	0.04	0.50	0.41	0.16	18.15	18.23	54.03	5.73	45.97	-40.01
GVZ	0.79	0.70	0.12	0.63	0.17	0.36	0.06	0.67	0.54	0.49	19.97	18.39	0.77	56.34	43.66	-14.39
$S^H_{\circ\leftarrow j}$	89.73	100.35	75.65	62.10	69.50	95.14	50.74	94.54	60.33	91.71	87.85	79.34	5.96	29.27	70.87	

Note: Each component is the estimated contribution of the volatility of cryptocurrency j to the variance of the 10-step-ahead forecast error of the volatility of cryptocurrency i. Model based on a VAR of order 1. $S^H_{\circ\leftarrow j}$ is the contribution from cryptocurrencies or market j to others, and $S^H_{i\leftarrow\circ}$ is the contribution from others to cryptocurrencies or market i. Finally, S^H_i corresponds to total volatility spillover indices.
Source: created by the authors

Impulse-response analysis

Additionally, using the VAR model estimates, an impulse-response analysis is performed between the realized volatility of cryptocurrencies and the implied volatility indices. Figure 5 and Figure 6 show the results with 95% confidence.

Figure 5 shows the impulse-response function of cryptocurrencies to a shock in the VIX and VSTOXX. It is possible to identify that a VIX shock generates a larger and more persistent impact over time than a VSTOXX shock. Moreover, for most cryptocurrencies the impulse-response function appears to stabilize around three months. Despite being minor, the results of a shock in VSTOXX elicit a negative response in cryptocurrencies such as Ethereum, XRP, DogeCoin, LitecCoin, and Stellar.

The impulse-response function of a shock to the implied volatility of oil and gold (OVX and GVZ) in cryptocurrencies is presented in Figure 6. The illustrations show that OVX generates a larger, negative response in all cryptocurrencies. In particular, a shock in GVZ appears to be smaller but more persistent over time than one from OVX.

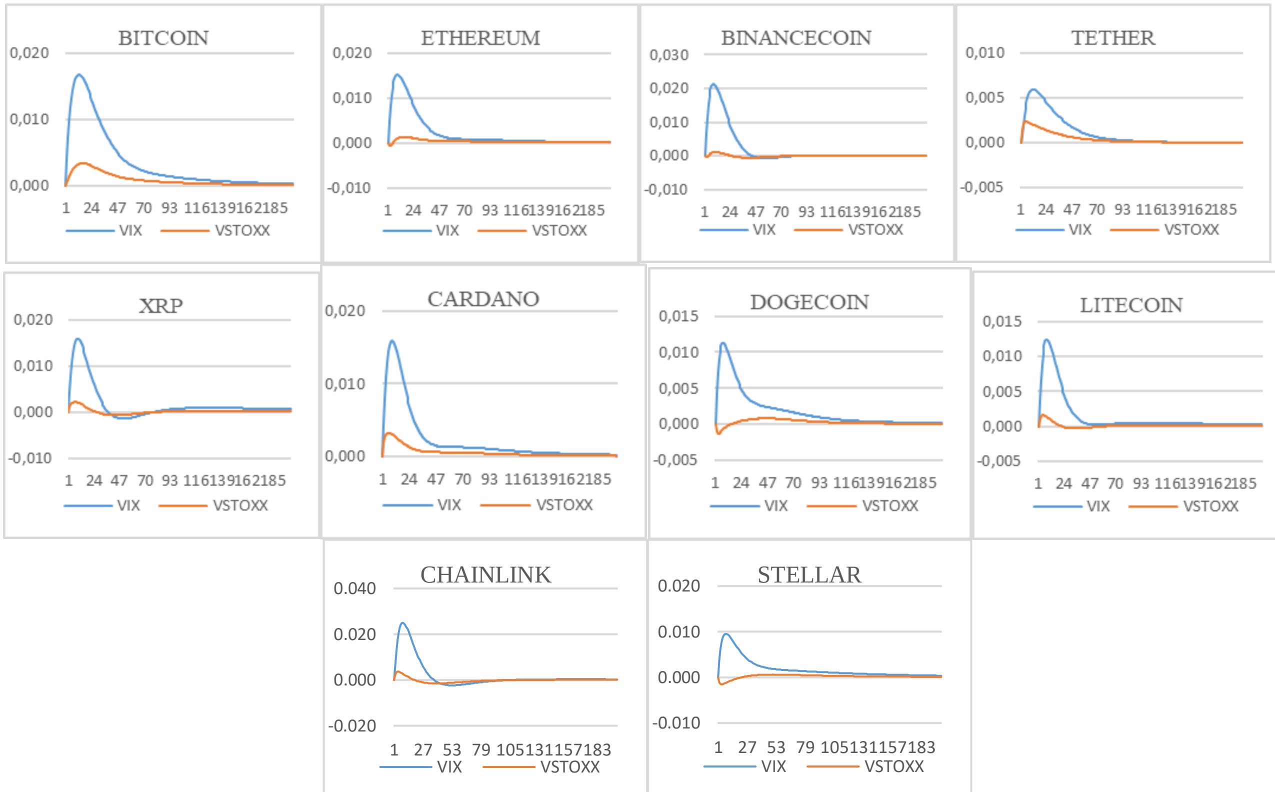

Figure 5. Momentum-Response analysis of the cryptocurrency market—VIX and VSTOXX shock
Source: created by the authors

http://dx.doi.org/10.22201/fca.24488410e.2023.3396

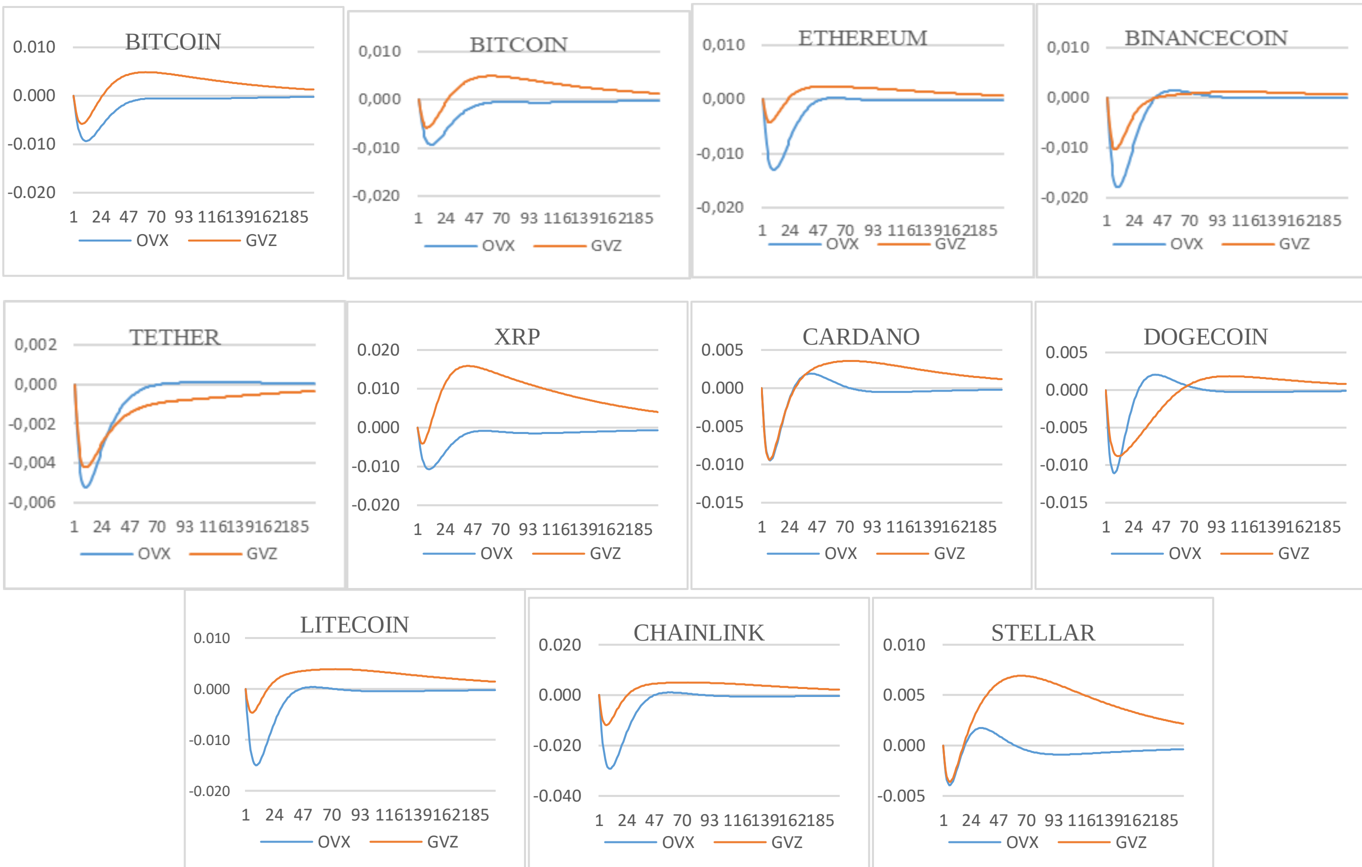

Figure 6. Momentum-Response Analysis of the cryptocurrency market—OVX and GVZ shock
Source: created by the authors

Conclusions

The cryptocurrency market has gained great popularity in recent years, and with the massive entry of different competitors, studying their relation has become a topic of great interest for investors. This study aims to analyze and identify the relation between the volatility of cryptocurrencies with the largest market capitalization and four implied volatilities representing the international financial markets and two commodities, using the spillover index from 2018 to 2020.

The findings of this research show that Bitcoin, despite being the oldest cryptocurrency with the largest market capitalization, is not positioned as the biggest volatility transmitter in the market. In this regard, it has been verified that the greatest effect is caused by Ethereum, Cardano, LiteCoin, and Stellar. These results imply and complement the way investors understand financial risk management, demonstrating that in periods of greater turbulence (2018 to 2020, for example) in the cryptocurrency market, the asset with the largest capitalization (Bitcoin) is not the only one that transmits volatility.

Looking at the implied volatility indices, it is found that they contribute to the volatility of cryptocurrencies, particularly VIX and VSTOXX, in amounts of less than 3%, which agrees with the findings of other authors. Furthermore, the indices associated with commodities, OVX and GVZ, do not contribute significantly to the volatility of cryptocurrencies.

These findings, for both financial and commodity markets, do not present a major connection to cryptocurrencies, which makes it highly attractive to investors as a potential tool for portfolio diversification and hedging strategies in the event of a shock in the cryptocurrency market.

Impulse-response analysis confirms the relation between financial markets and commodities about the realized volatility of cryptocurrencies. Specifically, the VIX has a greater impact on cryptocurrencies than the VSTOXX. Furthermore, when studying commodities, both generate a negative response to cryptocurrencies. The OVX generates a greater impact than the GVZ, while the GVZ has a greater persistence over time.

Finally, it is necessary to consider the limitation of the sample used, where cryptocurrencies within the top ten with the largest market capitalization are not considered due to the reduced availability of observations. Future lines of development may also consider a shorter analysis time and extend the spillover to domain frequency approaches or connections with emerging markets.

References

Akyildirim, E., Corbet, S., Lucey, B., Sensoy, A., y Yarovaya, L. (2020). The relationship between implied volatility and cryptocurrency returns. Finance Research Letters, 33, 101212. https://doi.org/10.1016/j.frl.2019.06.010

Antonakakis, N., Chatziantoniou, I., y Gabauer, D. (2019). Cryptocurrency market contagion: Market uncertainty, market complexity, and dynamic portfolios. Journal of International Financial Markets, Institutions and Money, 61, 37–51. https://doi.org/10.1016/j.intfin.2019.02.003

Balli, F., Bruin, A. de, Chowdhury, M. I. H., y Naeem, M. A. (2020). Connectedness of cryptocurrencies and prevailing uncertainties. Applied Economics Letters, 27(16), 1316–1322. https://doi.org/10.1080/13504851.2019.1678724

Barndorff-Nielsen, O. E., y Shephard, N. (2002). Econometric analysis of realized volatility and its use in estimating stochastic volatility models. Journal of the Royal Statistical Society: Series B (Statistical Methodology), 64(2), 253–280. https://doi.org/10.1111/1467-9868.00336

Baur, D. G., Hong, K. J., y Lee, A. D. (2015). Bitcoin – Currency or Asset? (SSRN Scholarly Paper No ID 2736020). Rochester, NY: Social Science Research Network. Recuperado de Social Science Research Network website, disponible en: https://papers.ssrn.com/abstract=2736020, consultado: 09/06/2021

Brauneis, A., y Mestel, R. (2018). Price discovery of cryptocurrencies: Bitcoin and beyond. Economics Letters, 165, 58–61. https://doi.org/10.1016/j.econlet.2018.02.001

Corbet, S., Meegan, A., Larkin, C., Lucey, B., y Yarovaya, L. (2018). Exploring the dynamic relationships between cryptocurrencies and other financial assets. Economics Letters, 165, 28–34. https://doi.org/10.1016/j.econlet.2018.01.004

Demirer, M., Diebold, F. X., Liu, L., y Yilmaz, K. (2018). Estimating global bank network connectedness. Journal of Applied Econometrics, 33(1), 1–15. https://doi.org/10.1002/jae.2585

Diebold, F. X., y Yilmaz, K. (2012). Better to give than to receive: Predictive directional measurement of volatility spillovers. International Journal of Forecasting, 28(1), 57–66. https://doi.org/10.1016/j.ijforecast.2011.02.006

Diebold, F. X., y Yılmaz, K. (2014). On the network topology of variance decompositions: Measuring the connectedness of financial firms. Journal of Econometrics, 182(1), 119–134. https://doi.org/10.1016/j.jeconom.2014.04.012

Diebold, F. X., y Yılmaz, K. (2015). Financial and Macroeconomic Connectedness: A Network Approach to Measurement and Monitoring. Oxford University Press. https://doi.org/10.1093/acprof:oso/9780199338290.001.0001

Dwita Mariana, C., Ekaputra, I. A., y Husodo, Z. A. (2020). Are Bitcoin and Ethereum safe-havens for stocks during the COVID-19 pandemic? Finance Research Letters, 101798. https://doi.org/10.1016/j.frl.2020.101798

Dyhrberg, A. H. (2016a). Bitcoin, gold and the dollar – A GARCH volatility analysis. Finance Research Letters, 16, 85–92. https://doi.org/10.1016/j.frl.2015.10.008

Dyhrberg, A. H. (2016b). Hedging capabilities of bitcoin. Is it the virtual gold? Finance Research Letters, 16, 139–144. https://doi.org/10.1016/j.frl.2015.10.025

Elsayed, A. H., Gozgor, G., y Yarovaya, L. (2022). Volatility and return connectedness of cryptocurrency, gold, and uncertainty: Evidence from the cryptocurrency uncertainty indices. Finance Research Letters, 47, 102732. https://doi.org/10.1016/j.frl.2022.102732

Fang, F., Ventre, C., Basios, M., Kanthan, L., Martinez-Rego, D., Wu, F., y Li, L. (2022). Cryptocurrency trading: A comprehensive survey. Financial Innovation, 8(1), 13. https://doi.org/10.1186/s40854-021-00321-6

Forbes, K. J., y Rigobon, R. (2002). No Contagion, Only Interdependence: Measuring Stock Market Comovements. The Journal of Finance, 57(5), 2223–2261. https://doi.org/10.1111/0022-1082.00494

Fousekis, P., y Tzaferi, D. (2021). Returns and volume: Frequency connectedness in cryptocurrency markets. Economic Modelling, 95, 13–20. https://doi.org/10.1016/j.econmod.2020.11.013

Gandal, N., Hamrick, J., Moore, T., y Oberman, T. (2018). Price manipulation in the Bitcoin ecosystem. Journal of Monetary Economics, 95, 86–96. https://doi.org/10.1016/j.jmoneco.2017.12.004

Garman, M. B., y Klass, M. J. (1980). On the Estimation of Security Price Volatilities from Historical Data. The Journal of Business, 53(1), 67–78. Disponible en: https://www.jstor.org/stable/2352358, consultado: 18/04/2021

Ghorbel, A., Loukil, S., y Bahloul, W. (2022). Connectedness between cryptocurrencies, gold and stock markets in the presence of the COVID-19 pandemic. European Journal of Management and Business Economics, ahead-of-print(ahead-of-print). https://doi.org/10.1108/EJMBE-10-2021-0281

Gillaizeau, M., Jayasekera, R., Maaitah, A., Mishra, T., Parhi, M., y Volokitina, E. (2019). Giver and the receiver: Understanding spillover effects and predictive power in cross-market Bitcoin prices. International Review of Financial Analysis, 63, 86–104. https://doi.org/10.1016/j.irfa.2019.03.005

Gronwald, M. (2019). Is Bitcoin a Commodity? On price jumps, demand shocks, and certainty of supply. Journal of International Money and Finance, 97, 86–92. https://doi.org/10.1016/j.jimonfin.2019.06.006

Ji, Q., Bouri, E., Lau, C. K. M., y Roubaud, D. (2019). Dynamic connectedness and integration in cryptocurrency markets. International Review of Financial Analysis, 63, 257–272. https://doi.org/10.1016/j.irfa.2018.12.002

Kristjanpoller, W., y Bouri, E. (2019). Asymmetric multifractal cross-correlations between the main world currencies and the main cryptocurrencies. Physica A: Statistical Mechanics and Its Applications, 523, 1057–1071. https://doi.org/10.1016/j.physa.2019.04.115

Kumar, A. S., y Anandarao, S. (2019). Volatility spillover in crypto-currency markets: Some evidences from GARCH and wavelet analysis. Physica A: Statistical Mechanics and Its Applications, 524, 448–458. https://doi.org/10.1016/j.physa.2019.04.154

Moratis, G. (2021). Quantifying the spillover effect in the cryptocurrency market. Finance Research Letters, 38, 101534. https://doi.org/10.1016/j.frl.2020.101534

Okorie, D. I., y Lin, B. (2020). Crude oil price and cryptocurrencies: Evidence of volatility connectedness and hedging strategy. Energy Economics, 87, 104703. https://doi.org/10.1016/j.eneco.2020.104703

Symitsi, E., y Chalvatzis, K. J. (2018). Return, volatility and shock spillovers of Bitcoin with energy and technology companies. Economics Letters, 170, 127–130. https://doi.org/10.1016/j.econlet.2018.06.012

TradingView. (2021). TradingView: Total Crypto Market Capitalization and Volume. Recuperado 15 de abril de 2021, de TradingView website: https://www.tradingview.com/markets/cryptocurrencies/global-charts/

Umar, Z., Trabelsi, N., y Alqahtani, F. (2021). Connectedness between cryptocurrency and technology sectors: International evidence. International Review of Economics & Finance, 71, 910–922. https://doi.org/10.1016/j.iref.2020.10.021

Yi, S., Xu, Z., y Wang, G.-J. (2018). Volatility connectedness in the cryptocurrency market: Is Bitcoin a dominant cryptocurrency? International Review of Financial Analysis, 60, 98–114. https://doi.org/10.1016/j.irfa.2018.08.012

Zięba, D., Kokoszczyński, R., y Śledziewska, K. (2019). Shock transmission in the cryptocurrency market. Is Bitcoin the most influential? International Review of Financial Analysis, 64, 102–125. https://doi.org/10.1016/j.irfa.2019.04.009