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Asymmetric connectedness between conventional and Islamic cryptocurrencies: Evidence from good and bad volatility spillovers

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Abstract
This paper examines the dynamics of the asymmetric volatility spillovers across four major cryptocurrencies comprising nearly 61% of cryptocurrency market capitalization and covering both conventional (Bitcoin and Ethereum) and Islamic (Stellar and Ripple) cryptocurrencies. Using a novel time-varying parameter vector autoregression (TVP-VAR) asymmetric connectedness approach combined with a high frequency (hourly) dataset ranging from 1st June 2018 to 22nd July 2022, we find that (i) good and bad spillovers are time-varying; (ii) bad volatility spillovers are more pronounced than good spillovers; (iii) a strong asymmetry in the volatility spillovers exists in the cryptocurrency market; and (iv) conventional cryptocurrencies dominate Islamic cryptocurrencies. Specifically, Ethereum is the major net transmitter of positive volatility spillovers while Stellar is the main net transmitter of negative volatility spillovers.

Keywords: Cryptocurrencies, TVP-VAR, Dynamic connectedness, Asymmetric connectedness, Volatility spillovers

Introduction

The rapid emergence of cryptocurrency as a new asset class offering high returns coupled with high volatility attracting both, individual and institutional investors has evoked a debate among policymakers, regulators, and bankers on its future position within the global financial system. Since the inception of Bitcoin in 2009, the cryptocurrency market has experienced a rough ride comprising steep uptrends and sharp price corrections. Several cryptocurrencies have emerged since then, relying on some key features of the blockchain technology of the oldest and largest cryptocurrency, Bitcoin.[1] While many cryptocurrencies have attracted the attention of speculators, a few major cryptocurrencies such as Bitcoin and Ethereum have gained significant ground among investors, practitioners, and international corporations.

[1] To obtain an in-depth understanding of blockchain technology, readers are directed to Xu et al. (2019).

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The rough ride in the short history of Bitcoin and other major cryptocurrencies has been the subject of numerous studies on their financial and economic aspects. Numerous studies consider the return transmission among major cryptocurrencies (see, Antonakakis et al. 2019; Ferreira et al. 2020; Nie 2020; Papadimitriou et al. 2020; Qureshi et al. 2020; Urom et al. 2020; Wang and Ngene 2020; Bouri et al. 2021, 2021; Khelifa et al. 2021; Pham et al. 2022; Ren and Lucey 2022b, a). While Koutmos (2018) and Wang and Ngene (2020) confirm the dominance of Bitcoin, Antonakakis et al. (2019) and Papadimitriou et al. (2020) show that large cryptocurrencies such as Bitcoin are not necessarily the most influential. Antonakakis et al. (2019) and Qureshi et al. (2020) argue that Ethereum has become a trivial source of market contagion.

Less attention has been paid to the volatility spillovers across cryptocurrencies (Katsiampa et al. 2019a; Bouri et al. 2020).[2] Notably, these studies focus on aggregate volatility and overlook the separation of volatility into good and bad measures, which has been the subject of recent studies on global stock markets (see, Bouri and Harb 2022). Good volatility reflects the variability of positive returns, whereas bad volatility captures the variability of negative returns. Accordingly, market participants do not treat these two facets of volatility similarly given that bad volatility is particularly harmful to the positions of long-purchasers whereas short-sellers appreciate bad volatility. In contrast, long purchasers appreciate good volatility as it reflects the variability of returns when the asset is appreciating. In the context of cryptocurrencies and in the presence of the "fear of missing out" phenomenon, good volatility tends to cluster in bull markets as traders and investors chase winning cryptocurrencies, which can accentuate price appreciation and feed good volatility. On the opposite side of the coin, cryptocurrency traders tend to sell cryptocurrencies under sharp turnarounds, which was the case during the sharp bear markets following the intensified regulatory scrutiny of Bitcoin and other major cryptocurrencies and the recent collapse of the FTX exchange. This suggests that the interconnectedness of cryptocurrency volatility is not necessarily similar during market downturns and market upturns, and thus the propagation of bad volatility differs from that of good volatility, leading to asymmetric volatility spillovers. Surprisingly, the academic literature remains silent on this issue, which is the subject of our current study.

Other studies of cryptocurrency spillovers often rely on the connectedness measures introduced by Diebold and Yılmaz (2012, 2014). For example, Koutmos (2018) shows not only significant and time-varying return and volatility spillovers across several cryptocurrencies, reflecting an intensifying degree of market contagion, but also evidence that Bitcoin is central to the system of spillovers. In the study of Antonakakis et al. (2019), a time-varying parameter factor-augmented vector autoregression (TVP-FAVAR) is used to measure the degree of contagion among cryptocurrencies. The findings reveal that contagion varies strongly over time and that, instead of Bitcoin, Ethereum is the main net transmitter of shocks. Corbet et al. (2018) investigate return and volatility spillovers in the time and frequency domains for Bitcoin, Ripple, and Litecoin showing that Litecoin and Ripple have a substantial impact on Bitcoin, whereas Bitcoin has a marginal

[2] Katsiampa et al. (2019a) apply bivariate Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models and find evidence of significant volatility dynamics and correlations among Bitcoin, Ethereum, and Litecoin. Bouri et al. (2020) find that the volatilities of cryptocurrencies significantly Granger cause each other in the frequency domain, suggesting a feedback effect.

influence on the others. Corbet et al. (2018), Koutmos (2018), Yi et al. (2018), and Ji et al. (2019) argue that Bitcoin is the dominant player in the cryptocurrency network.

The above-mentioned studies reveal important aspects of the spillover dynamics across cryptocurrency volatility. However, they overlook potential asymmetry in the dynamics of volatility spillovers arising from the difference in the spillover effect between good volatility and bad volatility. This is important in light of the recent spike in the price and volatility of Bitcoin and the universe of cryptocurrencies in late December 2020 and early 2021, during which their prices reached new all-time highs. To the best of our knowledge, no previous study has examined asymmetric volatility spillovers using high-frequency data. In order to accurately estimate asymmetric volatility spillovers, we employ a novel TVP-VAR asymmetric connectedness approach that extends the original framework of Baruník et al. (2016, 2017) with the TVP-VAR model of Koop and Korobilis (2014). This framework is less sensitive to outliers, does not require an arbitrarily chosen rolling window size, does not lose observations, and captures parameter changes more accurately (Antonakakis et al. 2020). Additionally, we incorporate the group-specific connectedness measures of Gabauer and Gupta (2018) to investigate the dynamics among conventional and Islamic cryptocurrencies.

Accordingly, the aim of this study is to investigate the good and bad volatility spillovers across various cryptocurrencies. Notably, we consider two groups of cryptocurrencies, Islamic and conventional. Islamic cryptocurrencies, in contrast to conventional cryptocurrencies, are cutting-edge technologies supported by real assets and distinguished by their core principles (Mnif and Jarboui 2021). In other words, these Islamic inventions, unlike conventional cryptocurrencies, contain tangible financial factors that underpin their pricing. As a result, their volatility and speculation are limited by these qualities (Berentsen and Schär 2018; Mnif et al. 2022). Stellar is the first distributed ledger protocol to achieve Sharia compliance from the Shariah Review Board licensed by the Central Bank of Bahrain in the money transfer and asset tokenization space. Ripple is a blockchain-based network that facilitates international cross-border payments. It employs cryptocurrency tokens that enable the conversion of all other currencies to a single currency known as XRP. Ripple always maintains the consortium or member banks' currency conversion rate. The Ripple network is particularly open in terms of providing the sender bank's liquidity status (Islam et al. 2022; Jani 2018). Notably, Bitcoin and Ethereum are the most well-known conventional cryptocurrencies with the highest market capitalization in the crypto market.

In spite of the fact that some studies discuss the interaction between Islamic metal-backed cryptocurrencies and conventional cryptocurrencies, and the potential for cryptocurrencies to become more suitable for Islamic finance (Abubakar et al. 2019; Alam et al. 2019; Ayedh et al. 2020; Houssem and Robbana 2019; Kakkattil 2019; Yousaf and Yarovaya 2022), this paper is motivated by some gaps in the literature. Firstly, as a purely cryptographic asset, Bitcoin can be transacted and used effectively as a method of payment, however, it does not seem to be universally accepted by Islamic (faith-based) retailers or investors looking for opportunities and businesses that adhere to Shariah (Mnif et al. 2022). It is pertinent to consider using a powerful tool based on modern financial technology to satisfy the demand for Islamic financial instruments and contracts, which would not only be compatible with Islamic Shariah laws but also be accepted in global financial transactions. A macro-payment platform such as Ripple and a micro-payment system like Stellar have the potential to become recognized in the Islamic finance industry as highly effective instruments in financial operations. The total market value of the Islamic finance industry is $2.2 trillion in 2020, catering to nearly a quarter of the world population's financial needs (Global Ratings 2022b). Additionally, Global Ratings (2022a) carries a forecast that the global Islamic finance industry will experience double-digit growth in total assets in 2022–2023 after a 10.2% growth in total assets in 2021. Islamic investors are highly motivated to use Shariah-compliant financial arrangements as part of their investment relationships and given that Shariah-compliant investments are similar to conventional ethical-investment principles (Williams and Zinkin 2010), it is likely that we could include investors who follow ethical values (moral, religious and social) in the Muslim target group. As a consequence, it is imperative not only that faith-based cryptocurrencies are introduced to the financial ecosystem, along with Islamic financial studies to enhance their public acceptance and social position, but also that the asymmetric volatility spillovers between Islamic and conventional cryptocurrencies must be explored to understand how return fluctuations, and particularly, decomposed volatilities (good and bad) are transmitted between these markets.

In regards to the second gap, it is vital to keep in mind that, traditionally, Islamic portfolios would only be diversified using Shariah-aligned assets (Alahouel and Loukil 2021; Aloui et al. 2015; Maghyereh et al. 2018, 2019; Trabelsi 2019; Yousaf and Yarovaya 2022), but as the most recent innovations in finance reveal, crypto assets have become a popular choice among portfolio managers during the COVID-19 crisis (Conlon et al. 2020; Corbet et al. 2020; Mariana et al. 2021; Goodell and Goutte 2021; Huang et al. 2021; Iqbal et al. 2021; Yousaf and Yarovaya 2022). This suggests that using Shariah-compliant cryptocurrencies may Muslim investors manage portfolio risk in a more effective manner, in particular during times of crisis. Nonetheless, any shocks generated by conventional cryptocurrencies to their Islamic counterparts during crisis times or normal periods may pose a threat to investors who add Shariah-compliant cryptocurrencies to their portfolios. However, in spite of this, there is no literature exploring the possibility of good and bad volatility spillovers between conventional cryptocurrencies and Islamic cryptocurrencies.

As a third point, there are a few studies on the interaction of Islamic and conventional cryptocurrencies, but all of them are designed based on three gold-backed Shariah-compliant cryptocurrencies, OneGram Coin, X8X Token, and HelloGold (see, Wasiuzzaman et al. 2022; Yousaf and Yarovaya 2022; Mnif et al. 2022; Aloui et al. 2021; Mnif and Jarboui 2021; Ali et al. 2022). As the market capitalization data compiled by coinranking.com on October 15, 2022 shows, OneGram, X8X, and HelloGold are 7670th, 6670th, and 2251st among cryptocurrencies, respectively, while the rankings of Ripple and Stellar are 6th and 26th, respectively. So, these crypto assets with significant market capitalization ($24.31 billion for Ripple and $2.28 billion for Stellar), coupled with their fame and popularity in the crypto market, make them two of the most prominent Islamic crypto assets, but their roles in contributing to the crypto market as Shariah-approved cryptocurrencies are almost invisible.

The fourth gap is largely due to the fact that Ripple and Stellar are two of the most widely accepted bank-based cryptocurrency platforms based on blockchain technology, that can be used by investors, traders, institutions, and industries to facilitate official transactions without involving the time-wasting mechanisms of the Society for Worldwide Interbank Financial Telecommunications (SWIFT) or Single Euro Payments Area (SEPA) (Kim et al. 2019; Lokhava et al. 2019; Mazieres 2015; Qiu et al. 2019). As a result, they are two of the most influential players in the digital payment network industry, even when it comes to purchasing conventional assets and trading crypto assets (see, Fang et al. 2022; Sebastião and Godinho 2021). Moreover, the volatility transitions between Islamic and conventional cryptocurrencies have profound implications for investors, big-tech companies, financial advisors for banks, asset managers, and regulators of financial markets.

Lastly, Islamic cryptocurrencies are less sensitive to global geopolitical risks because they comply with Shariah rules (Aloui et al. 2021). Additionally, the fact that Bitcoin and Ethereum are currently leading the charge for cryptocurrencies (Demir et al. 2021; Sifat et al. 2019), may pose some risks for Shariah-compliant cryptocurrencies. Therefore, the overall impact of volatility transitions from conventional cryptocurrencies to Islamic cryptocurrencies is not yet clear.

We contribute to the academic literature on the cryptocurrency spillover effect in various ways. Firstly, to the best of our knowledge, this is the first study to examine the asymmetric volatility spillovers and resulting interconnectedness across major cryptocurrencies using high-frequency data. It nicely extends the works of Katsiampa et al. (2019a), Bouri et al. (2020), Koutmos (2018), Corbet et al. (2018), Yi et al. (2018), and Ji et al. (2019). Secondly, our study focuses on the cryptocurrency market, comparing the two conventional cryptocurrencies with the highest market values and two Islamic cryptocurrencies. As far as we know, this is the only study to examine cryptocurrency volatility, taking into account the division between conventional and Islamic cryptocurrencies, during the COVID-19 pandemic, using the wavelet coherence approach and nonlinear Granger causality test. It is worth noting the study of Raza et al. (2022), which uses the same methodology, but with no specific classification of cryptocurrencies analyzed (only market capitalization is taken into account). Cao and Xie (2022) also take the TVP-VAR connectedness approach to investigate the asymmetric dynamic spillover effect between cryptocurrency and China's financial market, showing that, while the influence of China's financial market on cryptocurrencies is very small, the impact of cryptocurrencies (Bitcoin, Ethereum, and Ripple) on China's financial market is rather high.

Our results indicate that disentangling good and bad volatility leads to a deeper and more nuanced understanding of volatility transmission in the cryptocurrency markets. We find that the dynamic total connectedness is time-varying and dependent on economic events. Furthermore, bad volatility spillovers are more pronounced than good volatility spillovers, suggesting that cryptocurrencies tend to be more interconnected during market downturns than upturns. We also provide further evidence on the decreasing role and importance of Bitcoin, to the detriment of Ethereum which is in line with Antonakakis et al. (2019) and Ji et al. (2019). Stellar is the main net transmitter of negative volatility shocks. Interestingly, Ripple is at the receiving end of both, positive and negative spillovers. Finally, we find strong empirical evidence that conventional cryptocurrencies dominate Islamic cryptocurrencies. This effect is stronger for negative volatility spillovers.

The remainder of this study is structured as follows: Sect. "Data" describes the underlying data; Sect. "Methodology" outlines the methodology employed; Sect. "Empirical results" presents and discusses the results; and Sect. "Concluding remarks" concludes.

Data

In this study, we use the hourly closing prices of Bitcoin (BTC), Ethereum (ETH), Ripple (XRP), and Stellar (XLM). In accordance with Wen et al. (2022), Hu et al. (2019), Ma and Tanizaki (2022) and Sifat et al. (2019), and taking into account the limitations of time coverage of observations made with high and low frequency in different databases, as well as the limitations of time coverage of intraday observations, our analysis is carried out based on hourly data collected between 2018.06.01, 00:00:00, and 2022.07.22, 05:00:00, comprising more than 36,000 data records.

According to Urquhart and Zhang (2019), who also use hourly frequency for Bitcoin prices, higher frequency data is very suitable. Zhang et al. (2019) demonstrate that using prices at hourly intervals for four major cryptocurrencies (Bitcoin, Ethereum, Ripple, and Litecoin) is relatively efficient compared to other frequencies. Similar to Hu et al. (2019), Wen et al. (2022), Wang and Ngene (2020), and Urquhart and Zhang (2019), data are gathered from the Bitstamp exchange, which is one of the oldest, most popular, and most liquid exchanges (Brandvold et al. 2015). Bitstamp is one of the exchanges most trusted by participants in the global market (Bouri et al. 2017).

Our analysis covers a period when the cryptocurrency market passed through major booms and collapses. We have 9,218 and 27,006 hly observations, respectively, in the periods before and after Bitcoin reached $10,000 for the first time on June 21, 2019. It is worth mentioning that the sample period includes the entire COVID-19 pandemic of 2020-2022, the historical peak of Bitcoin of $68,626.49 on 11 November 2021, the period of new mining regulations and rules in China at the end of 2021, and the start of 2022, global cycles of interest rate hikes starting in 2022, and the Russia-Ukraine war starting in February 2022.

Four main reasons inspired the decision to select BTC, ETH, XRP, and XLM as the cryptocurrencies for study. Firstly, in terms of market capitalization and traded volume, they account for a significant share of the market, with market capitalizations of $452.1 billion, $198.6 billion, $17.9 billion, and $2.9 billion, respectively, making up more than 61% of the cryptocurrency market, which has a market capitalization of $1,084.78 billion as of July 21, 2022.[3] The second advantage of using these cryptocurrencies is that they tend to be the most liquid, due to the volume of trading (Mensi et al. 2021). This means manipulation of prices is much more complex and challenging and, by extension, the conclusions of empirical studies are much stronger and better established (Bouri et al. 2020). Thirdly, the unprecedented success of Bitcoin's underlying technology and its ability to sustain rapid development has led to the emergence of many cryptocurrencies, including Ethereum, Ripple, and Stellar, which have quickly grown in market size, become prominent players in the market, and act as alternative digital assets (Bouri et al. 2019). The majority of other cryptocurrencies are based on Bitcoin's blockchain, but seek

[3] https://coinmarketcap.com. and https://www.statista.com/statistics/730876/cryptocurrency-maket-value/.

to remedy some of the deficiencies of Bitcoin (Youssef and Zenner 2020), for instance, its lack of stability and scalability[4] (Dark et al. 2019). Stellar and Ripple have both experienced quite stable bear markets, especially between January 2015 and March 2017 (Kristoufek and Vosvrda 2019). Bitcoin is characterized by its speculative nature and the diversification of its uses, and Ethereum is characterized by its professional and complementary attributes. Meanwhile, Ripple is controlled by a large group of banks and is able to assume professional and diversification functions, Stellar holds a pre-eminent place in the cryptocurrency market as an intermediation asset between professional, technical, and speculative groups (Ahelegbey et al. 2021). Fourthly, BTC and ETH have the largest market capitalization of conventional cryptocurrencies, while XRP and XLM, which adhere to Shariah rules, have the highest market capitalization among Shariah-compliant cryptocurrencies. It may be possible to draw relevant comparisons between faith-based crypto assets and conventional crypto assets based on these categories. Stellar is one of 28 blockchain projects chosen for evaluation by a scientific institution affiliated with China's Ministry of industry and information technology. A large adoption in China may trigger a chain reaction in which businesses around the world embrace the Stellar blockchain. The inclusion of Stellar is particularly significant, since it may inspire other nations with harsher attitudes towards cryptocurrency to follow the same path. In a globalized world, the acts of one nation, particularly one as powerful as China, are likely to be emulated by others. If there were to be a widespread acceptance of cryptocurrency, Stellar is ideally positioned to ride this wave of adoption (RJet 2018).

Finally, as a similar decentralized payment system, Ripple uses credit networks as its foundation. This means there are no restrictions on who is allowed to deploy a Ripple instance since the code is open source and available to anyone (Ghosh et al. 2007; Schwartz et al. 2014). As a result of collaborations with over 200 organizations, including large banks, payment providers, and some central banks, Ripple has achieved significant results, including providing currency to investors in Islamic countries (Rella 2020). At the Global Islamic Economy Summit in Dubai in October 2018, the Global Head for Infrastructure Innovation at Ripple, while delivering the keynote presentation, pointed out that Ripple aligns well with Islamic finance principles, and the Middle East's transition to blockchain is a positive way to encourage innovation in the region (Summit 2018). For example, Rain, a Bahrain-based cryptocurrency exchange currently graduating from the sandbox of the Shariyah Review Bureau (SRB), is the latest platform to offer Ripple trading pairs. The Sharia advisory committee of SRB, licensed by the central bank of Bahrain, has conducted a Sharia analysis of Ripple, indicating that the token has Shariah-compliant functionality, and can be considered Shariah-compliant for practical use (Bureau 2022). The SRB recognizes the Stellar technology and network as the first distributed ledger protocol that complies with Sharia law and has granted a certificate in this respect, which also applies to the applications and uses of Lumens (Rabbani et al. 2020). The certificate states that the Stellar network concept and principle include no cases that are contradictory to Sharia standards, and it can be deemed Sharia compliant as it contains the principle of "the original state of things". When assets are sold in

[4] A system's scalability refers to its capacity to grow and evolve to meet the needs of the users.

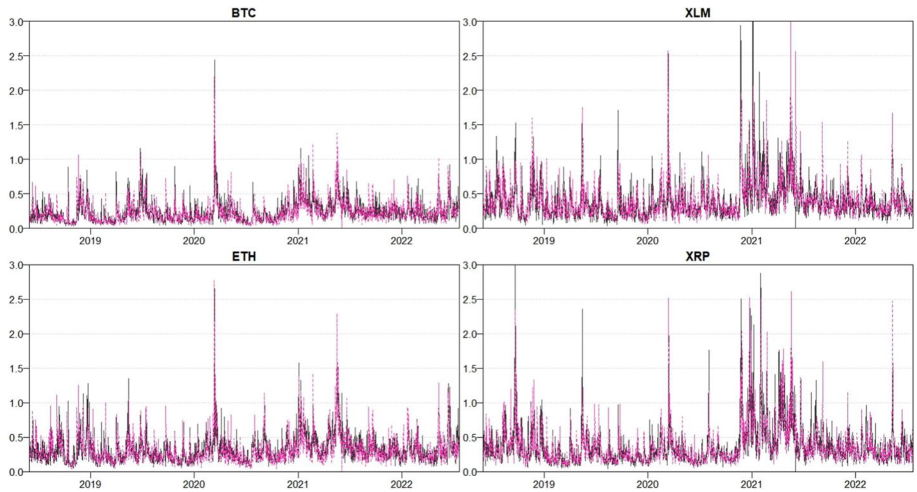


Fig. 1 Positive and negative absolute returns. *Notes*: The black line represents the positive absolute returns while the green one represents the negative absolute returns

this network, the person transferring credit to the buyer can reclaim the credit from a trust line and repurchase the actual asset (Foundation 2018a). This license should aid the expansion of the Stellar ecosystem in areas where financial services must adhere to Islamic finance standards (Foundation 2018b).

In the first stage of data preparation, we compute hourly returns for each price series as $y_t = \frac{x_t - x_{t-1}}{x_{t-1}}$ due to the non-stationary nature of cryptocurrency prices, which is formally tested by the ERS unit-root test (Elliott et al. 1996).

Secondly, we compute daily positive and negative absolute returns using the following concept[5]:

$$z_t = \frac{1}{T}\sum_{t=1}^{T}|y_t| \tag{1}$$

$$z_t = \left(\frac{1}{T}\sum_{t=1}^{T}(1-S_t)|y_t|\right) + \left(\frac{1}{T}\sum_{t=1}^{T}S_t|y_t|\right) \tag{2}$$

$$S_t = \begin{cases} 0, & \text{if } y_t < 0 \\ 1, & \text{if } y_t \geq 0 \end{cases} \tag{3}$$

$$z_t = z_t^+ + z_t^- \tag{4}$$

where y_t stands for the hourly percentage changes and T is the number of observations per day. Thus, z_t denotes the average daily absolute percentage change which is the sum of the daily positive absolute return, z_t^+, and the daily negative absolute return, z_t^-. Figure 1 illustrates both the positive and negative absolute returns for each series.

[5] Baruník et al. (2016) use positive and negative semivariances for the asymmetric connectedness approach, however, as squaring values often generates outliers, we focus on average absolute returns to overcome this issue.

Table 1 Summary statistics

	BTC^{+}	ETH^{+}	XLM^{+}	XRP^{+}	BTC^{-}	ETH^{-}	XLM^{-}	XRP^{-}
Mean	0.241***	0.324***	0.397***	0.371***	0.235***	0.316***	0.393***	0.365***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Variance	0.029***	0.045***	0.091***	0.100***	0.031***	0.051***	0.074***	0.087***
Skewness	2.989***	2.507***	3.862***	3.382***	2.929***	2.927***	2.940***	3.252***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Ex.Kurtosis	21.676***	13.705***	29.521***	17.754***	17.074***	16.587***	15.382***	16.054***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
JB	31875***	13426***	58700***	22756***	20542***	19505***	17095***	18915***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ERS	− 8.611***	− 9.046***	− 9.115***	− 8.853***	− 8.892***	− 10.256***	− 10.754***	− 7.759***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$Q(20)$	1697.923***	1645.724***	1238.341***	1822.990***	1627.654***	1276.062***	1226.728***	1671.705***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$Q^2(20)$	337.824***	560.779***	353.678***	613.898***	662.026***	556.729***	430.976***	558.797***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Kendall τ	BTC^{+}	ETH^{+}	XLM^{+}	XRP^{+}	BTC^{-}	ETH^{-}	XLM^{-}	XRP^{-}
BTC^{+}	1.000***	0.594***	0.400***	0.282***	0.359***	0.261***	0.207***	0.280***
ETH^{+}	0.594***	1.000***	0.467***	0.308***	0.264***	0.293***	0.222***	0.297***
XLM^{+}	0.400***	0.467***	1.000***	0.323***	0.217***	0.230***	0.378***	0.311***
XRP^{+}	0.282***	0.308***	0.323***	1.000***	0.257***	0.268***	0.293***	0.448***
BTC^{-}	0.359***	0.264***	0.217***	0.257***	1.000***	0.664***	0.509***	0.271***
ETH^{-}	0.261***	0.293***	0.230***	0.268***	0.664***	1.000***	0.578***	0.289***
XLM^{-}	0.207***	0.222***	0.378***	0.293***	0.509***	0.578***	1.000***	0.318***
XRP^{-}	0.280***	0.297***	0.311***	0.448***	0.271***	0.289***	0.318***	1.000***

*** Denotes significance level at 1%; Skewness: D'Agostino (1970) test; Kurtosis: Anscombe and Glynn (1983) test; JB: Jarque and Bera (1980) normality test; ERS: Elliott et al. (1996) unit-root test; $Q(20)$ and $Q^2(20)$: Fisher and Gallagher (2012) weighted portmanteau test

The summary statistics of positive and negative absolute returns are shown in Table 1. Interestingly, all average positive volatilities are slightly larger than negative volatilities. Furthermore, all series are positively skewed and leptokurtic distributed which means all series are significantly non-normally distributed at the 1% significance level (Jarque and Bera 1980). All series are stationary according to the ERS unit-root test (Elliott et al. 1996), significantly autocorrelated, and exhibit GARCH errors. The Kendall rank correlation coefficients reveal that the highest correlations occur between negative absolute returns. Notably, all correlation coefficients are between 0.207 and 0.664. These statistics show that our methodological concept of modeling the cryptocurrency interdependencies using a TVP-VAR model with time-varying variance-covariances is adequate.

Methodology

In the next step, the positive and negative absolute returns are used to estimate good and bad volatility spillovers, respectively. For this purpose, we employ the TVP-VAR connectedness approach of Antonakakis et al. (2020). Particularly, we are estimating a TVP-VAR(1) model as suggested by the Bayesian Information Criterion (BIC):

$$\boldsymbol{z}_t = \boldsymbol{B}_t \boldsymbol{z}_{t-1} + \boldsymbol{u}_t \qquad \boldsymbol{u}_t \sim N(\boldsymbol{0}, \boldsymbol{S}_t) \tag{5}$$

$$vec(\boldsymbol{B}_t) = vec(\boldsymbol{B}_{t-1}) + \boldsymbol{v}_t \qquad \boldsymbol{v}_t \sim N(\boldsymbol{0}, \boldsymbol{R}_t) \tag{6}$$

where $\boldsymbol{z}_t$, $\boldsymbol{z}_{t-1}$ and $\boldsymbol{u}_t$ are $k \times 1$ dimensional vectors in t, $t-1$, and the corresponding error term, respectively. $\boldsymbol{B}_t$ and $\boldsymbol{S}_t$ are $k \times k$ dimensional matrices demonstrating the TVP-VAR coefficients and the time-varying variance-covariances while $vec(\boldsymbol{B}_t)$ and $\boldsymbol{v}_t$ are $k^2 \times 1$ dimensional vectors and $\boldsymbol{R}_t$ is a $k^2 \times k^2$ dimensional matrix. Finally, the TVP-VAR is transformed to a time-varying parameter vector moving average (TVP-VMA) using the Wold representation theorem: $\boldsymbol{z}_t = \sum_{i=1}^{p} \boldsymbol{B}_{it} \boldsymbol{z}_{t-i} + \boldsymbol{u}_t = \sum_{j=0}^{\infty} \boldsymbol{A}_{jt} \boldsymbol{u}_{t-j}$.

Subsequently, the TVP-VMA coefficients are used to compute the Generalized Forecast Error Variance Decomposition (GFEVD) of Koop et al. (1996) and Pesaran and Shin (1998). The H-step ahead GFEVD models the impact a shock in series j has on series i. This can be formulated as follows,

$$\phi_{ij,t}^{gen}(H) = \frac{\sum_{h=0}^{H-1} (\boldsymbol{e}_i' \boldsymbol{A}_{ht} \boldsymbol{\Sigma}_t \boldsymbol{e}_j)^2}{(\boldsymbol{e}_j' \boldsymbol{\Sigma}_t \boldsymbol{e}_j) \sum_{h=0}^{H-1} (\boldsymbol{e}_i' \boldsymbol{A}_{ht} \boldsymbol{\Sigma}_t \boldsymbol{A}_{ht}' \boldsymbol{e}_i)} \tag{7}$$

$$gSOT_{ij,t} = \frac{\phi_{ij,t}^{gen}(H)}{\sum_{l=1}^{k} \phi_{il,t}^{gen}(H)} \tag{8}$$

where $\boldsymbol{e}_i$ is a $k \times 1$ dimensional zero vector with unity on its ith position. As the $\phi_{ij,t}^{gen}(H)$ stands for the unscaled GFEVD ($\sum_{j=1}^{K} \zeta_{ij,t}^{gen}(H) \neq 1$), Diebold and Yılmaz (2009, 2012, 2014) suggested normalizing it by dividing $\phi_{ij,t}^{gen}(H)$ by the row sums to obtain the scaled GFEVD, $gSOT_{ij,t}$.

The scaled GFEVD is at the center of the connectedness approach facilitating the computation of the total directional connectedness to (from) all series. While the TO total directional connectedness constitutes the effect series i has on all others, the FROM total directional connectedness illustrates the impact all series have on series i. These connectedness measures can be calculated by,

$$S^{gen,to}_{i\to\bullet,t} = \sum_{j=1,i\neq j}^{k} gSOT_{ji,t} \tag{9}$$

$$S^{gen,from}_{i\leftarrow\bullet,t} = \sum_{j=1,i\neq j}^{k} gSOT_{ij,t}. \tag{10}$$

By computing the difference between the TO and the FROM total directional connectedness, we obtain the NET total directional connectedness of series i:

$$S^{gen,net}_{i,t} = S^{gen,to}_{i\to\bullet,t} - S^{gen,from}_{i\leftarrow\bullet,t}. \tag{11}$$

If $S^{gen,net}_{i,t} > 0$ ($S^{gen,net}_{i,t} < 0$), series i is influencing (influenced by) all others more than being influenced by (influencing) them and thus is considered to be a net transmitter (receiver) of shocks indicating that series i is driving (driven by) the network.

The connectedness approach also provides information on the bilateral level. The net pairwise directional connectedness shows the bilateral net transmission of shocks between series i and j,

$$S^{gen,net}_{ij,t} = gSOT_{ji,t} - gSOT_{ij,t}. \tag{12}$$

If $S^{gen,net}_{ij,t} > 0$ ($S^{gen,net}_{ij,t} < 0$), series i dominates (is dominated by) series j implying that series i influences (is influenced by) series j more than being influenced by (influencing) it.

The Total Connectedness Index (TCI) is another relevant metric highlighting the degree of network interconnectedness and hence market risk. Considering that the TCI can be calculated as the average total directional connectedness to (from) others, it is equal to the average amount of spillovers one series transmits (receives) from all others. Chatziantoniou and Gabauer (2021) and Gabauer (2021) have shown that as the own variance shares are by construction always larger or equal to all cross variance shares the TCI is within $\left[0, \frac{k-1}{k}\right]$. To obtain a TCI which is within [0,1], we have to slightly adjust the TCI:

$$gSOI_t = \frac{1}{k-1}\sum_{i=1}^{K} S^{gen,from}_{i\leftarrow\bullet,t} = \frac{1}{k-1}\sum_{i=1}^{k} S^{gen,to}_{i\to\bullet,t}, \tag{13}$$

A high (low) value indicates high (low) market risk.

Finally, we calculate the Pairwise Connectedness Index (PCI) which can be seen as the TCI on the bilateral level illustrating the degree of interconnectedness between series i and j. This can be formulated as:

$$PCI_{ij,t} = 2\left(\frac{gSOT_{ij,t} + gSOT_{ji,t}}{gSOT_{ii,t} + gSOT_{ij,t} + gSOT_{ji,t} + gSOT_{jj,t}}\right), \qquad 0 \leq PCI_{ij,t} \leq 1. \tag{14}$$

Table 2 Averaged positive/negative connectedness table

	BTC	ETH	XLM	XRP	FROM
BTC	51.43 (41.50)	30.70 (31.62)	15.33 (24.30)	2.54 (2.58)	48.57 (58.50)
ETH	29.51 (31.03)	48.56 (39.48)	18.64 (26.44)	3.30 (3.04)	51.44 (60.52)
XLM	16.71 (23.41)	20.64 (26.12)	57.63 (45.67)	5.01 (4.80)	42.37 (54.33)
XRP	12.87 (16.29)	16.67 (18.76)	24.36 (26.67)	46.10 (38.28)	53.90 (61.72)
TO	59.09 (70.73)	68.01 (76.50)	58.33 (77.41)	10.85 (10.42)	TCI
NET	10.52 (12.23)	16.57 (15.98)	15.96 (23.09)	− 43.05 (− 51.30)	65.43 (78.36)

Results are based on a TVP-VAR model with a lag length of order 1 (BIC) and a 20-step-ahead generalized forecast error variance decomposition (Antonakakis et al. 2020). Values in parentheses represent negative connectedness measures while others represent positive connectedness measures

The interpretation is identical to the TCI but on a bilateral level.[6]

Empirical results

Averaged dynamic connectedness measures

We start with an explanation of the good and bad averaged dynamic connectedness measures. The results in Table 2 show that the total connectedness index (TCI) related to negative spillovers (78.36%) is greater than the TCI related to positive spillovers (65.43%). This indicates that negative volatility spillovers have a more pronounced effect on the connectedness system than positive volatility spillovers. Moreover, this is the case for all cryptocurrencies as BTC (58.50%>48.57%), ETH (60.52%>51.44%), XLM (54.33%>42.37%), and XRP (61.72%>53.90%) are influenced more by bad volatility spillovers. For example, BTC transmits 59.09% of a shock to all others and receives 48.57% of shocks from all others, for positive volatility spillovers, while BTC transmits 70.73% of a shock to all others and receives 58.50% of a shock from all others, for negative volatility spillovers. Thus, the own-variance share - on the diagonal - is consistently lower for all cryptocurrencies for negative volatility spillovers than positive volatility spillovers.

ETH is the main net transmitter of positive volatility shocks (16.57%), while Stellar is the main net transmitter of negative volatility shocks (23.09%). Interestingly, in both scenarios ETH dominates BTC which is in line with the findings of Antonakakis et al. (2019) and Ji et al. (2019).

Dynamic total connectedness

As the averaged TCI shown in Table 2 masks the dynamics over time, we examine the dynamic total connectedness illustrated in Fig. 2. We observe that both negative and positive dynamic total connectedness are time-varying and highly correlated with each other. Both range between 45% and 95%. The highest level of total connectedness occurred in the early 2020 s, during the COVID-19 outbreak, while the lowest interconnectedness occurred at the end of 2018 when there was a severe drop in cryptocurrency prices. According to Berentsen and Schär (2018) this dynamic fluctuation can be explained by the fact that cryptocurrencies are decentralized and have a relatively

[6] The analysis was conducted with the R package "Connectedness Approach" of Gabauer (2022).

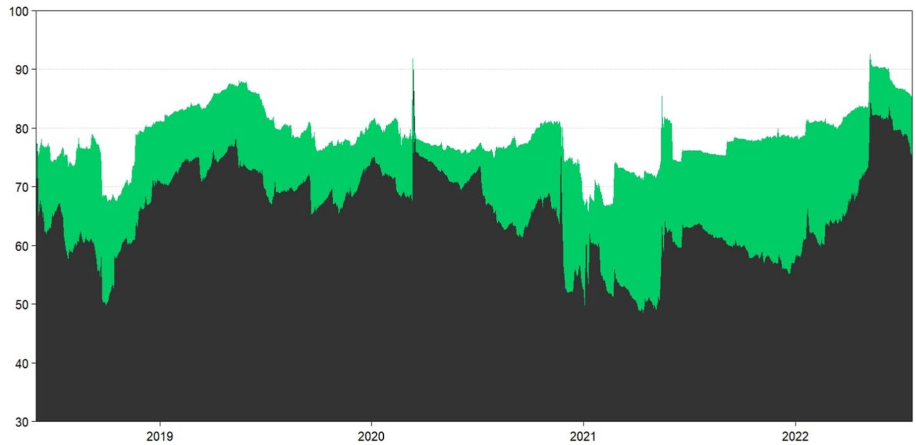


Fig. 2 Dynamic total connectedness. Notes: Results are based on a TVP-VAR model with a lag length of order 1 (BIC) and a 20-step-ahead generalized forecast error variance decomposition (Antonakakis et al. 2020). The black area represents the positive connectedness measures while the green one represents the negative ones

determined supply. Thus, they are significantly vulnerable to short-term changes. Another explanation is provided by Antonakakis et al. (2019) who claim that the formation of Ethereum and Ripple and the subsequent development in their transaction volumes might drive market interconnectedness.

Asymmetric total connectedness

To illustrate the degree of asymmetry in the crypto market, we calculate the differences between bad and good total dynamic connectedness. If ΔTCI is greater than zero it indicates that bad volatility spillovers affect the network more than good volatility spillovers. As shown in Fig. 3, and in line with Ji et al. (2019), negative TCI is always higher than positive TCI, showing that the volatility of cryptocurrencies is more interconnected via negative (bad) than positive (good) volatility spillovers. This indicates a strong connection during the cryptocurrency market decline. However, it is worth noting the very brief period around the outbreak's announcement when the positive TCI exceeded the negative TCI. This indicates that, for that brief time, positive (good) volatility spillovers had a greater impact on cryptocurrency volatility than negative (bad) volatility spillovers. In particular, from early 2020 to the end of 2021, there is a more pronounced asymmetry between good and bad dynamic total connectedness, with a difference of more than 20%. In other words, the asymmetries between spillovers resulting from negative and positive volatility become 20%, but the size of the asymmetry does not imply the amount of the spillovers themselves. Asymmetry is a measure of how responsive the market is to good or bad news and serves as a reliable predictor of the expectations and attitudes of the market. This visualization provides further evidence that negative news, such as the severe drop in cryptocurrency prices in 2018, the outbreak of COVID-19 at the beginning of 2020, or the crypto collapse in May 2021, have a more pronounced effect on cryptocurrency interconnectedness. Differences in volatility spillovers caused by bad and good volatility are important since they have notably different long-term implications.

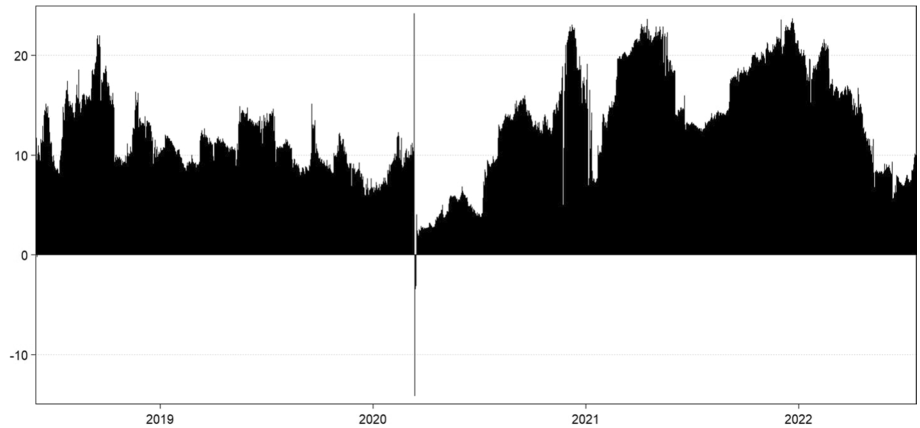


Fig. 3 Difference between positive and negative dynamic total connectedness. Notes: Results are based on a TVP-VAR model with a lag length of order 1 (BIC) and a 20-step-ahead generalized forecast error variance decomposition (Antonakakis et al. 2020)

Net total directional connectedness

Next, we look at the dynamic net total directional connectedness illustrated in Fig. 4, in order to discriminate between net transmitters and net receivers of shocks in the cryptocurrency market.

Notably, XRP is the main net receiver of volatility shocks while all others are net transmitters. Interestingly, we observe that XLM is a stronger net transmitter of bad volatility spillovers until mid-2021, while BTC decreases significantly at the end of 2020 when it recovers quickly. To be more precise, positive volatility spillovers outnumber bad volatility spillovers for BTC and ETH through to the end of 2020. However, after that time, negative volatility spillovers exceed positive volatility spillovers. This indicates that bad news has a greater impact on BTC and ETH after the end of 2020. One probable explanation is that following the COVID-19 outbreak in early 2020, many individuals began considering cryptocurrencies as an inflation hedge and possible safe haven (Choi and Shin 2022; Conlon et al. 2021), leading to a boom in trading activity and value in late 2020. Accordingly, some research suggests that market asymmetries created by illogical transactions and the herding behavior of uneducated traders account for sharp increases in volatility, and make negative return shocks more severe (Kakinaka and Umeno 2022).

Another cause might be the newly established regulations against cryptocurrencies by governments and financial institutions throughout the world, which express worry over the potential threats presented by digital assets, including money laundering, fraud, and market manipulation (Chokor and Alfieri 2021; Bonaparte and Bernile 2022). XLM, on the other hand, experienced the reverse phenomenon after early 2021, when positive news began to outweigh negative news.

It should be noted that, even though BTC, ETH, and XLM are net transmitters of shocks, it is clear that BTC decreases in its power over time, while the other two become pronounced net transmitters of shocks by the end of the sample period.

Our results are supported by Ji et al. (2019), who find Litecoin and Stellar to be the two main net transmitters of shocks. Shahzad et al. (2021) analyze low and high volatility regime-dependent cryptocurrency spillovers and find that XLM is the main net

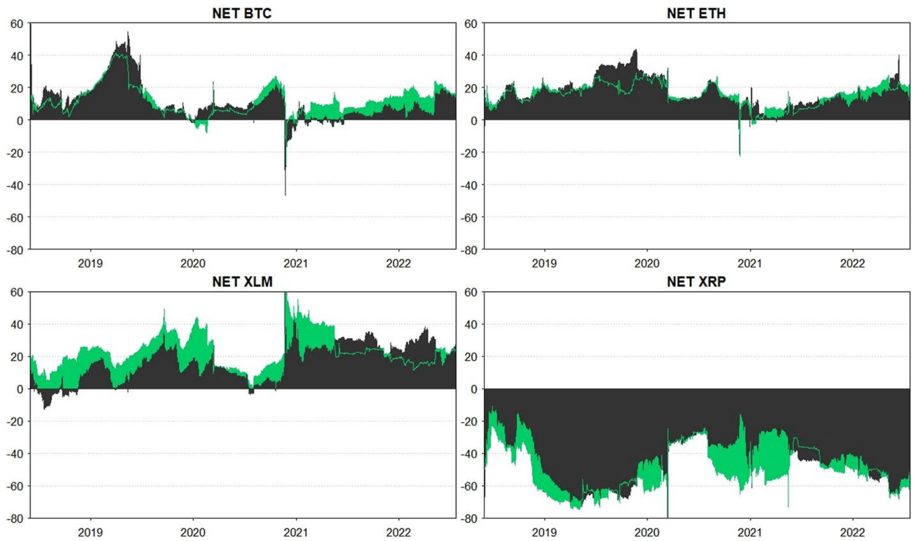


Fig. 4 Net total directional connectedness. Notes: Results are based on a TVP-VAR model with a lag length of order 1 (BIC) and a 20-step-ahead generalized forecast error variance decomposition (Antonakakis et al. 2020). The black line represents the positive connectedness measures while the green one represents the negative ones

transmitter of shocks in both regimes, while BTC plays only a minor role. Antonakakis et al. (2019) point out that ETH has become more important than BTC.

Net pairwise directional connectedness

To get a more in-depth explanation of the net total directional connectedness, we examine the net pairwise directional connectedness illustrated in Fig. 5. The net pairwise directional connectedness measures allow us to pinpoint the specific position of every given pair and determine which series primarily transmit (receive) volatility spillover effects in net terms.

The empirical results show that BTC is except at the beginning of the sample period, dominated by ETH. The relationship between ETH and XLM illustrates that ETH dominates XLM in terms of positive volatility spillovers, while the opposite is true for negative volatility spillovers. Notably, BTC significantly dominates XLM at the beginning of the sample period, but XLM starts to overtake BTC in mid-2019, which lasts until the beginning of 2022. At the end of the period, the roles appear to change frequently, which implies that XLM and BTC have similar relevance. All the cryptocurrencies clearly dominate XRP. Of specific interest is the relationship between the two Islamic cryptocurrencies, where XLM appears to be the main net transmitter of shocks to XRP.

Dynamic pairwise connectedness

Table 3 shows that our chosen cryptocurrencies are highly correlated, implying a strong bilateral interconnectedness among BTC, ETH, XLM, and XRP. This result is not surprising given that cryptocurrencies belong to the digital asset class, share common technological features, and are often subject to the same global risk factors (see, Bouri et al. 2020; Qureshi et al. 2020; Ji et al. 2019). Furthermore, we see that all pairwise connectedness indices are higher in the bad volatility spillover scenario. We find that ETH and BTC

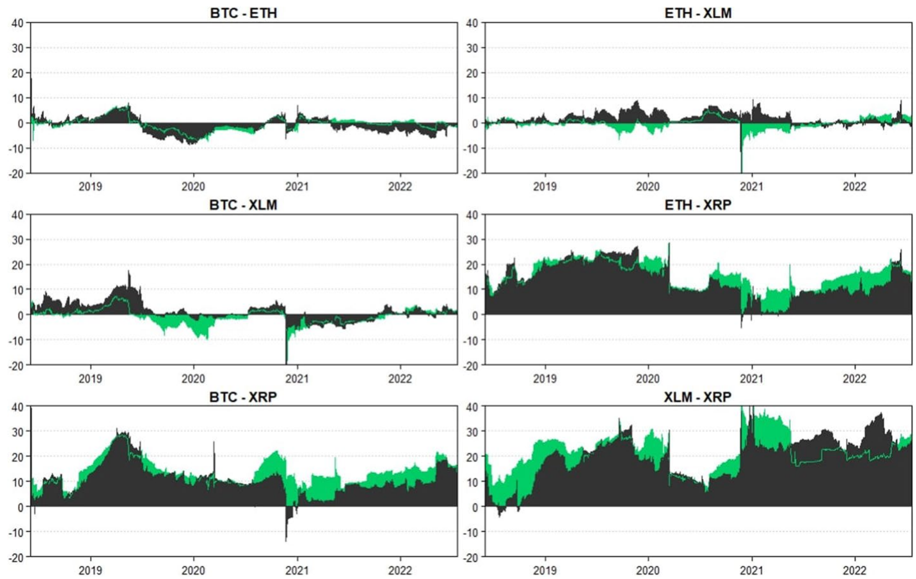


Fig. 5 Net pairwise directional connectedness. Notes: Results are based on a TVP-VAR model with a lag length of order 1 (BIC) and a 20-step-ahead generalized forecast error variance decomposition (Antonakakis et al. 2020). The black line represents the positive connectedness measures while the green one represents the negative ones

have the highest interconnectedness (75.44%, 87.22%) while BTC and XRP have the lowest interconnectedness (27.66%, 38.77%). Although the finding of the highest dynamic pairwise connectivity is consistent with Ji et al. (2019), the lowest connectedness they find is between ETH and XRP. Since XLM and XRP are both Shariah-compliant cryptocurrencies, we expected them to be highly interrelated, however, the results suggest that they are not strongly associated (44.07%, 54.79%).

As Table 3 represents only averaged measures, which mask the time-varying dynamics, we turn to Fig. 6 which shows strong and similar co-movements among all four cryptocurrencies. We identify two common troughs of connectedness at the end of 2018 and 2021 and one common maximum at the beginning of 2020. Interestingly, the interconnectedness between ETH and BTC as well as between XLM and XRP, stays rather constant after the end of 2020, while the pairwise connectedness values for XLM and XRP drop sharply. It appears as if BTC and ETH become more strongly connected, as would be expected in a common market, while XLM and XRP create a second market. It is also worth noting that negative connectedness significantly outweighs positive connectedness between XLM and the traditional cryptocurrencies suggesting that the connection is more strongly related to bad news than good news. A similar scenario occurs after 2021 but with less significance and connection between XRP and conventional cryptocurrencies.

Group-specific connectedness measures

Finally, we focus on the group-specific connectedness measures to identify the connectedness dynamics between the conventional and Islamic cryptocurrencies (see, Gabauer and Gupta 2018). Figure 7 illustrates the interconnectedness within each conventional and Islamic cryptocurrency (left) and between the conventional and Islamic

Table 3 Averaged positive/negative pairwise connectedness table

	BTC	ETH	XLM	XRP
BTC	100.00 (100.00)	75.44 (87.22)	45.64 (70.81)	27.66 (38.77)
ETH	75.44 (87.22)	100.00 (100.00)	54.29 (76.41)	35.5 (44.33)
XLM	45.64 (70.81)	54.29 (76.41)	100.00 (100.00)	44.07 (54.79)
XRP	27.66 (38.77)	35.5 (44.33)	44.07 (54.79)	100.00 (100.00)

Results are based on a TVP-VAR model with a lag length of order 1 (BIC) and a 20-step-ahead generalized forecast error variance decomposition (Antonakakis et al. 2020). Values in parentheses represent negative connectedness measures while others represent positive connectedness measures

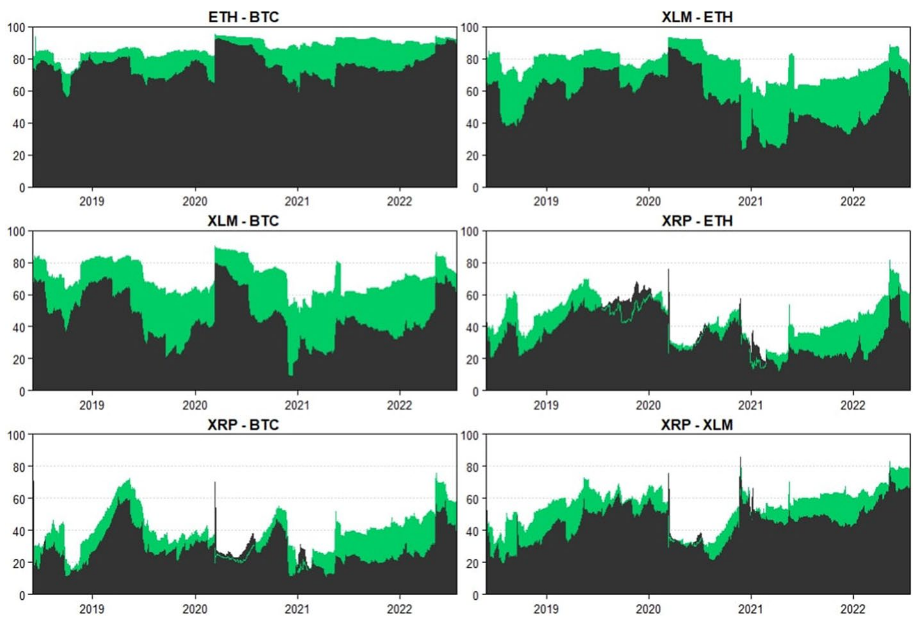


Fig. 6 Dynamic pairwise connectedness. Notes: Results are based on a TVP-VAR model with a lag length of order 1 (BIC) and a 20-step-ahead generalized forecast error variance decomposition (Antonakakis et al. 2020). The black line represents the positive connectedness measures while the green one represents the negative ones

cryptocurrencies (right). This indicates that, within each market, there is substantially higher interconnectedness than between the conventional and Islamic markets. Interestingly, negative volatility spillovers are constantly more pronounced in both scenarios than positive volatility spillovers.

Figure 8 shows the net group directional connectedness measures. The conventional cryptocurrency market strongly dominates the Islamic cryptocurrency market, except for a short period at the end of 2020. It should be noted that, until mid-2020, positive volatility spillovers are more pronounced than negative volatility spillovers, while afterward, negative volatility spillovers clearly dominate.

Robustness checks

To illustrate the robustness of our results, we compute various forecast horizons from 5 to 30 days for the TVP-VAR asymmetric connectedness approach employed. In addition,

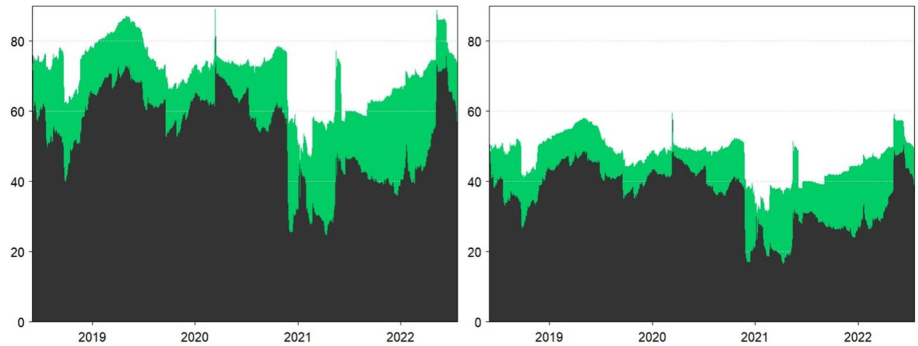


Fig. 7 Group-specific dynamic connectedness. Notes: Results are based on a TVP-VAR model with a lag length of order 1 (BIC) and a 20-step-ahead generalized forecast error variance decomposition (Antonakakis et al. 2020). The black and green areas represent the positive and negative group-specific dynamic connectedness

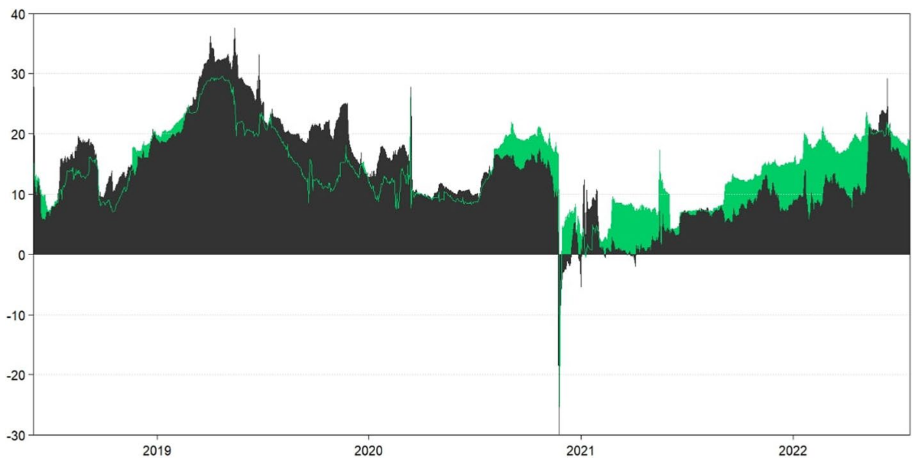
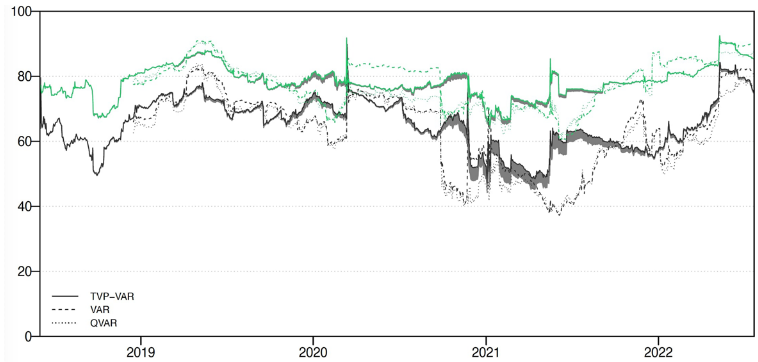


Fig. 8 Net group-specific directional connectedness. Notes: Results are based on a TVP-VAR model with a lag length of order 1 (BIC) and a 20-step-ahead generalized forecast error variance decomposition (Antonakakis et al. 2020). The black and green areas represent the positive and negative net group-specific directional connectedness

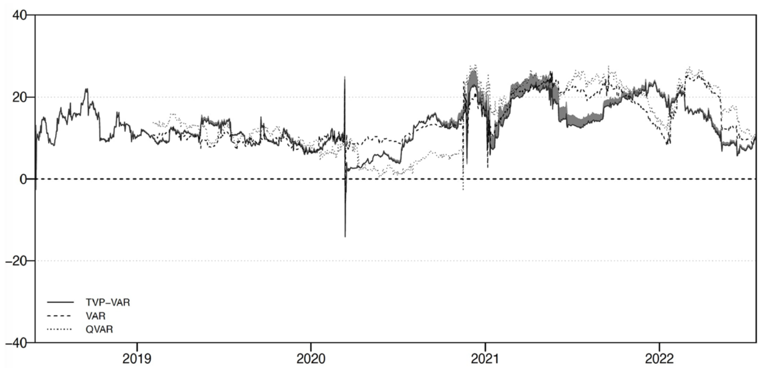
we compare the TVP-VAR-based connectedness measures with results obtained using 250-day rolling-window VAR (Diebold and Yılmaz 2012) and 250-day rolling-window qunatile vector autoregression (QVAR) (Chatziantoniou et al. 2021) models.

Figure 9 shows that various forecast horizons lead to only minor differences among all measures. The main differences occur between the autumn of 2020 and the end of 2021 and appear to be smaller for bad volatility spillovers than good volatility spillovers.

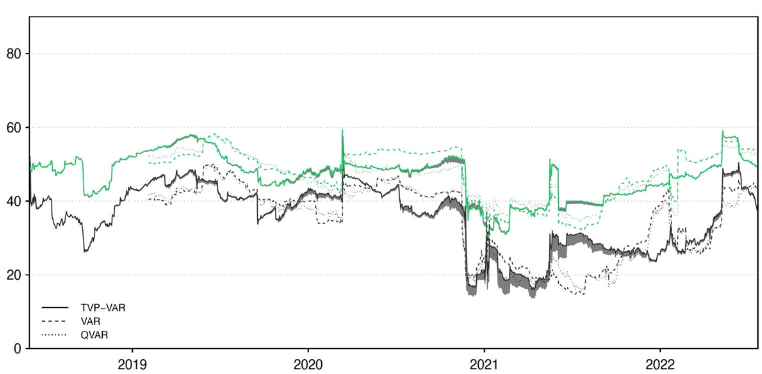
In Panel (a), we compare the dynamic total connectedness from the TVP-VAR approach to the VAR and QVAR results. While the dynamics behave similarly, they differ over some shorter periods. For instance, the QVAR and TVP-VAR models show a drop in the dynamic total connectedness at the end of 2020, while the VAR approach shows this decline occurring months earlier. As this trend is not shown by the QVAR approach, this difference can be explained by the fact that VAR models are more sensitive to outliers than the other two models. Also, between the spring and the end of 2021, the TVP-VAR measures differ from the others. Monte Carlo simulations conducted by Antonakakis et al. (2020) show that TVP-VAR results are more reliable than VAR results, and therefore we conclude that the TVP-VAR dynamics are



(a) Dynamic total connectedness



(b) Difference between positive and negative dynamic total connectedness



(c) Group-specific dynamic connectedness

Fig. 9 Robustness checks. Notes: In Panels (a) and (b), the black lines represent the good dynamic total and group-specific connectedness, respectively while the green lines highlight the bad dynamic total and group-specific connectedness. The solid line illustrates the results retrieved from the TVP-VAR-based connectedness approach (Antonakakis et al. 2020) which is compared to the rolling-window VAR (Diebold and Yılmaz 2012) and the rolling-window QVAR (Chatziantoniou et al. 2021) connectedness approach which is visualized using dashed and dotted lines, respectively. All models are based on a lag length of order 1 (BIC) and a 20-step-ahead generalized forecast error variance decomposition while the rolling-window approaches use a 250-day window representing the average annual trading days. Finally, the grey area represents the differences between the minimum and maximum dynamic total connectedness by adjusting the forecast horizon of the TVP-VAR approach (5 and 30 steps ahead) more accurate than the others. Another potential explanation for this difference could be the rolling window size of the VAR and QVAR frameworks, especially as the difference occurs for almost 250 days, which is the window size employed.

Panel (b) shows the asymmetric effects between bad and good total connectedness. Even though there are some deviations from the TVP-VAR connectedness measures, the main story remains the same, with all methods concluding that the dynamic total connectedness is higher for bad than good volatility spillovers.

Finally, Panel (c) shows the differences in the group-specific dynamic connectedness measures. Notably, in mid-2019 the dynamics obtained from the TVP-VAR appear months later in the VAR and QVAR framework. This is another indicator that the TVP-VAR connectedness approach adjusts faster and more accurately to changes in parameters. Additionally, the bad volatility spillover dynamics are more similar across the various models, while the group-specific dynamics of good volatility spillovers again differ in the period from mid-2021 to the end of 2021.

Thus, we conclude that our results are robust. Even though there are minor differences between the models, the results are qualitatively similar and tell the same story. The differences that occur can mainly be linked to the disadvantages of the VAR and QVAR approaches, which are: (i) smoothed-out parameter changes; (ii) outlier sensitivity in the case of VAR; and (iii) the chosen window size.

Concluding remarks

Considering the uniqueness of cryptocurrencies and the new investment opportunities they provide to traders and investors in terms of risk management and portfolio analysis, this research examines the dynamics of asymmetric volatility spillovers across four major cryptocurrencies, Bitcoin, Ethereum, Ripple, and Stellar, using intraday price data from May 31, 2018, to July 22, 2022. Our analysis shows the following results. Firstly, market interconnectedness is higher for negative volatility than positive volatility spillovers, indicating asymmetric volatility spillover behavior in the crypto market. Since traders react differently to positive and negative news, the split of volatility into positive and negative may be considered a measure of risk. Therefore, we infer from the results that the market becomes riskier as asymmetry increases. This result is strengthened by pairwise connectedness measures, which also show interconnectedness among negative volatility spillovers. Secondly, we demonstrate that the level of spillover transmission between the selected cryptocurrencies is not constant. The net total directional connectedness of each cryptocurrency in terms of the transmission mechanism, is quite different. Ethereum is the primary shock transmitter for good volatility spillovers while Stellar is the main shock transmitter for bad volatility spillovers. This emanates from two main characteristics that have helped Ethereum climb to the top of the market, having smart contracts and fast transactions. Thirdly, Bitcoin has lost its dominant power in the crypto market, which is in line with previous findings (see, Bouri et al. 2020; Ji et al. 2019; Katsiampa et al. 2019b, a; Antonakakis et al. 2019). This result can be explained by Chinaâ€™s major involvement in the Bitcoin system. Fourthly, conventional cryptocurrencies dominated Islamic cryptocurrencies throughout almost the entire period of investigation.

In terms of theoretical implications, this study extends the asymmetric volatility spillover literature by introducing a novel TVP-VAR asymmetric connectedness approach which augments the original framework of Baruník et al. (2016, 2017) with the TVP-VAR model of Koop and Korobilis (2014), to provide a more accurate picture of the transmission mechanism between cryptocurrencies offering new opportunities for future study. Furthermore, we add to the literature on the potential for positive and negative volatility spillovers between conventional cryptocurrencies and Islamic cryptocurrencies including Stellar and Ripple, which are not backed by gold. Our findings show that conventional cryptocurrencies, with both positive and negative volatility, almost always dominate Islamic cryptocurrencies.

Considering the practical implications, these findings are useful for risk and portfolio managers, as well as cryptocurrency traders or investors with interests in Islamic cryptocurrencies. The results identify the most influential cryptocurrencies in the system of both good and bad volatility spillovers. By understanding the volatility in the cryptocurrency market, people are able to make better investment decisions and develop their trading strategies. Furthermore, the time-varying nature of the results indicates the unsuitability of static (time-invariant) trading strategies and the need to discriminate good from bad volatility spillovers. Despite receiving Islamic certificates from the SRB, Ripple and Stellar have considerable asymmetry and are dominated by Bitcoin and Ethereum. As a result of our analysis, investors in Islamic cryptocurrency marketplaces should consider these two cryptocurrencies to be high-risk investments in their portfolios.

Portfolio managers can also use this information to assess the risk of their portfolios and make informed decisions about which cryptocurrencies to include. The time-varying nature of the results highlights the need for dynamic portfolio management strategies that can adapt to changes in the relationships between cryptocurrencies. Since Ethereum and Stellar are the main shock transmitters of good and bad volatility, respectively, it is better to have both in a portfolio to reduce risk. The results are especially enlightening when the market experiences a shock.

Additionally, policymakers can use the results of this study to take timely risk prevention action, by considering both positive and negative volatility spillovers due to market trending. In an upward trend, it is easy for hazards to accrue, thus vigilance is required. Conversely, in a downturn, risks are revealed, and appropriate action is required to avert losses. Hence, policymakers responsible for regulating the cryptocurrency market can use the results of this study to make informed decisions about how to reduce the risks associated with changes in one cryptocurrency affecting others.

Potential limitations of this study include the focus on two major conventional and Islamic cryptocurrencies, and a reliance on the TVP-VAR specification of Koop and Korobilis (2014). Future studies should consider a larger sample of Islamic cryptocurrencies to make the analysis more comprehensive for Sharia-compliant funds. Furthermore, future studies should also use alternative TVP-VAR specifications such as those proposed by Koop and Korobilis (2013), Del Negro and Primiceri (2015), or Petrova (2019).

Appendix

Technical appendix

The TVP-VAR is represented as follows,

$$\begin{aligned} \boldsymbol{z}_t &= \boldsymbol{B}_t \boldsymbol{z}_{t-1} + \boldsymbol{u}_t \quad \boldsymbol{u}_t \sim N(\boldsymbol{0}, \boldsymbol{S}_t) \\ vec(\boldsymbol{B}_t) &= vec(\boldsymbol{B}_{t-1}) + \boldsymbol{v}_t \quad \boldsymbol{v}_t \sim N(\boldsymbol{0}, \boldsymbol{R}_t) \end{aligned}$$

where $\boldsymbol{z}_t$, $\boldsymbol{z}_{t-1}$, and $\boldsymbol{u}_t$ represent $k \times 1$ dimensional vectors and $\boldsymbol{B}_t$ and $\boldsymbol{S}_t$ are $k \times k$ dimensional matrices. Furthermore, $vec(\boldsymbol{B}_t)$ and $\boldsymbol{v}_t$ are $k^2 \times 1$ dimensional vectors and $\boldsymbol{R}_t$ is an $k^2 \times k^2$ dimensional matrix.

An empirical Bayes prior is applied where the priors, $vec(\boldsymbol{B}_0)$ and $\boldsymbol{S}_0$, are equal to the estimation results of a constant parameter vector autoregression (VAR) estimation based on the full dataset.

$$\begin{aligned} vec(\boldsymbol{B}_0) &\sim N(vec(\boldsymbol{B}_{OLS}), \boldsymbol{R_{OLS}}) \\ \boldsymbol{S}_0 &= \boldsymbol{S}_{OLS}. \end{aligned}$$

The Kalman Filter estimation relies on forgetting factors ($0 \leq \kappa_i \leq 1$) which regulates how fast the estimated coefficients vary over time. If the forgetting factor is set equal to 1 the algorithm collapses to a constant parameter VAR. Since it is assumed that parameters are not changing dramatically from one day to another, κ_2 is set equal to 0.99:

$$\begin{aligned} vec(\boldsymbol{B}_t)|\boldsymbol{z}_{1:t-1} &\sim N(vec(\boldsymbol{B}_{t|t-1}), \boldsymbol{R}_{t|t-1}) \\ vec(\boldsymbol{B}_{t|t-1}) &= vec(\boldsymbol{B}_{t-1|t-1}) \\ \boldsymbol{R}_t &= (1 - \kappa_2^{-1})\boldsymbol{R}_{t-1|t-1} \\ \boldsymbol{R}_{t|t-1} &= \boldsymbol{R}_{t-1|t-1} + \boldsymbol{R}_t \end{aligned}$$

The multivariate EWMA procedure for $\boldsymbol{S}_t$ is updated in every step, while κ_1 and κ_2 are set equal to 0.99 based on the sensitivity results provided by Koop and Korobilis (2014). Furthermore, Koop and Korobilis (2014) fix the forgetting factors, as well, even if the forgetting factors can be estimated by the data, as in Koop and Korobilis (2013). The main reason to fix the parameters is twofold (i) it increases computational burden substantially and (ii) the value added to the forecasting performance is questionable.

$$\begin{aligned} \hat{\boldsymbol{u}}_t &= \boldsymbol{z}_t - \boldsymbol{B}_{t|t-1}\boldsymbol{z}_{t-1} \\ \boldsymbol{S}_t &= \kappa_1 \boldsymbol{S}_{t-1|t-1} + (1 - \kappa_1)\hat{\boldsymbol{u}}_t' \hat{\boldsymbol{u}}_t \end{aligned}$$

$vec(\boldsymbol{B}_t)$ and $\boldsymbol{R}_t$ are updated by

$$\begin{aligned} vec(\boldsymbol{B}_t)|\boldsymbol{z}_{1:t} &\sim N(vec(\boldsymbol{B}_{t|t}), \boldsymbol{R}_{t|t}) \\ vec(\boldsymbol{B}_{t|t}) &= vec(\boldsymbol{B}_{t|t-1}) + \boldsymbol{R}_{t|t-1}\boldsymbol{z}_{t-1}'(\boldsymbol{S}_t + \boldsymbol{z}_{t-1}\boldsymbol{R}_{t|t-1}\boldsymbol{z}_{t-1}')^{-1}(\boldsymbol{z}_t - \boldsymbol{B}_{t|t-1}\boldsymbol{z}_{t-1}) \\ \boldsymbol{R}_{t|t} &= \boldsymbol{R}_{t|t-1} + \boldsymbol{R}_{t|t-1}\boldsymbol{z}_{t-1}'(\boldsymbol{S}_t + \boldsymbol{z}_{t-1}\boldsymbol{R}_{t|t-1}\boldsymbol{z}_{t-1}')^{-1}(\boldsymbol{z}_{t-1}\boldsymbol{R}_{t|t-1}) \end{aligned}$$

Finally, the variances, $\boldsymbol{S}_t$, are updated by the EWMA procedure

$$\begin{aligned} \hat{\boldsymbol{u}}_{t|t} &= \boldsymbol{z}_t - \boldsymbol{B}_{t|t}\boldsymbol{z}_{t-1} \\ \boldsymbol{S}_{t|t} &= \kappa_1 \boldsymbol{S}_{t-1|t-1} + (1 - \kappa_1)\hat{\boldsymbol{u}}_{t|t}' \hat{\boldsymbol{u}}_{t|t} \end{aligned}$$

Abbreviations

BIC	Bayesian information criterion
BTC	Bitcoin
ETH	Ethereum
GARCH	Generalized autoregressive conditional heteroskedasticity
GFEVD	Generalized forecast error variance decomposition
PCI	Pairwise connectedness index
QVAR	Qunatile vector autoregression
SEPA	Single Euro payments area
SRB	Shariyah review bureau
SWIFT	Society for Worldwide Interbank Financial Telecommunications
TCI	Total connectedness index
TVP-FAVAR	Time-varying parameter factor-augmented vector autoregression
TVP-VAR	Time-varying parameter vector autoregression
TVP-VMA	Time-varying parameter vector moving average
VAR	Vector autoregression
XLM	Stellar
XRP	Ripple

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Declarations

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