



The connectedness and risk spillovers between bitcoin spot and futures markets: evidence from intraday data

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Abstract

This paper examines the dynamic relation between Bitcoin spot and futures markets during the Covid-19 pandemic. Using hourly data from 2020 combined with quantile impulse response analysis and predictability in the distribution test, we attempt to ascertain whether spot or futures markets lead in the price discovery process under a variety of market conditions. Granger predictability based on the left tail, the right tail, and the center of the distribution show bidirectional predictability between spot and futures markets suggesting significant feedback effects following normal and extreme gains/losses where neither market dominates in price discovery. Using a CAViaR model and the associated impulse response functions with estimates for dynamic tail dependence, we document spillovers between quantiles of spot and futures returns. Estimates of impulse response functions at various risk levels show the futures market has an edge in influencing the spot market and figures more prominently in the price discovery process.

Keywords Bitcoin returns · Cryptocurrencies · Futures markets · Risk spillovers · Information flows

JEL Classification E42 · G13 · G14 · G23

1 Introduction

In an ideal world, asset prices should reflect discounted cash flows and instantaneously react to the arrival of new information. However, in the real world this process is not smooth and explicit in some financial markets. Therefore, price developments in these markets demonstrate more sophisticated dynamics. As theory posits, financial asset prices evolve per liquidity

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(Pástor & Stambaugh, 2003), real interest rates (Grossman & Shiller, 1980), information-based trading (Easley et al., 2002), and changes in risk appetite and economic uncertainty (Baele et al., 2010; Bekaert et al., 2019). The cryptocurrency market, on the other hand, has shown that such factors are insignificant when accounting for token price fluctuations, as its market is highly speculative, volatile, and does not depict the characteristics of a medium of exchange (Baek & Elbeck, 2015; Balcilar et al., 2017; Baur et al., 2018; Ciaian et al., 2016; Guizani & Nafti, 2019). However, these findings can be attributed to the nature of the cryptocurrency market being in its infancy. Compared to stock and foreign exchange markets, it is clear that the cryptocurrency market is far from being established. The introduction of Bitcoin futures can be considered a milestone in its journey towards such an established market.

Both the Chicago Mercantile Exchange (CME) and the Chicago Board Options Exchange (CBOE) launched the Bitcoin futures contract in mid-December 2017. Bitcoin futures allow investors to trade in a regulated market with a more secure platform. Noteworthy exchange failures have shown that cryptocurrencies have a relatively high counterparty risk. However, in Bitcoin futures, the risk that stems from contractual obligations are alleviated through the margin deposit, the mark-to-market process, and by clearinghouses. Although the futures market's principal function is to hedge exposed risks in the spot market, the introduction of Bitcoin futures also offers transparency and price discovery for market participants. As discussed by Kavussanos et al. (2008), if interest rates and dividend yields follow a deterministic process, in a perfectly frictionless world, price developments of the spot and futures markets would exhibit a perfect positive correlation with no cross-autocorrelations. In such a world, both markets would be perfectly efficient, and in response to information arrivals, supply and demand curves would immediately intersect at a new equilibrium price with no lag. Therefore, investors would be indifferent to taking a position in the futures market. However, if the informed traders are prone to choose one of these markets over another, then the price development of that chosen market can govern the other (Chu et al., 1999). For example, Brooks et al. (2001) and Bohl et al. (2011) state that futures markets are likely to react to incoming information faster than spot markets due to their inherent leverage, high liquidity, low transaction costs, and fewer short-sale restrictions. These features make futures markets more dominant in the price discovery realm and account for the lead-lag relationship in returns. However, the evidence obtained from Bitcoin futures is not yet sufficient to define their price discovery function. Moreover, the differences between the trading hours of Bitcoin futures and its spot price may distort these widely accepted factors. For example, while cryptocurrencies in the spot market run 24/7, the trading hours of Bitcoin futures are 6:00 p.m.–5:00 p.m. ET and 6:00 p.m.–6:45 p.m. ET Sunday–Friday in the CME Globex and CME ClearPort, respectively (CME Group, 2022). From a statistical standpoint, sample specific features may lead to different results than those in the literature, which mostly examine conventional markets such as equity and foreign exchange. Work by Hajric (2019) shows that Bitcoin prices experience severe jumps during weekends, accounting for 40% of its returns from May 2019 to January 2020. This phenomenon may reduce the leading role of futures market's in transmitting information or change the direction of the lead-lag relationship in favor of the spot market. On the other hand, due to the utilization of futures market for both hedging and speculation purposes, it can be expected that in periods of high volatility, the return and volatility spillovers of Bitcoin may make the futures market more dominant than the spot market. This effect is expected to be more evident during crises, and thus the futures market may accentuate the volatility in underlying assets within such episodes. These phenomena also necessitate the examination of the relation between spot and futures prices under different market conditions.

While there is an extensive literature on such relationships with various results reported from different markets, studies that examine tail dependence in Bitcoin spot and futures markets in terms of price discovery are quite limited. As such, this study explores the lead-lag relation of futures and the spot markets for Bitcoin and attempts to account for any interactions. Such empirical findings can be potentially useful for traders who seek returns in the cryptocurrency market. Efficient Market Hypothesis supposes that all available information in the market is immediately incorporated into asset prices and that market participants cannot make abnormal profits. Therefore, in a truly efficient market, all assets are fairly valued, with none undervalued or overvalued. However, if the dissemination of information lags across markets, then traders may use this information to earn higher returns following the discovery by the transmitter and recipient, and after understanding the extent of the lag.

The paper aims to contribute to the existing literature in several aspects. First, there is no consensus about the direction of predictability in Bitcoin spot and futures markets where the dynamic relationship between spot and futures markets may be complex and hence requires further examination. Although some studies focus on nonlinear relationships between Bitcoin spot and futures markets, to the best of our knowledge, this is the first attempt to examine tail dependence between Bitcoin spot and futures markets. In this regard, this study first utilizes predictability in the distribution test suggested by Candelon and Tokpavi (2016), and then the quantile impulse responses analysis suggested by White et al. (2015), to better understand the dynamic relationship between Bitcoin spot and futures markets under different market conditions. To that end, the center, left, and right tail of the distribution for spot and futures return series is focused on, where segments of the distribution correspond to different market conditions such as normal, bearish, and bullish markets. Lahiani et al. (2021) pointed out several benefits of examining tail dependence between financial assets for policymakers, investors, and portfolio managers. For example, examining tail dependence of financial assets help investors and portfolio managers efficiently allocate their portfolios and make optimum investment decisions. As such, examining tail dependence between spot and futures markets is vital for risk management purposes as the main function of a futures market is to hedge risks stemming from the spot market. Also, Koutmos (2020), Corbet et al. (2021), and Maghyreh and Abdoh (2020) found that the relationship between Bitcoin and financial assets (such as stock, commodity, gold, foreign exchange, and bond markets) is different under different market conditions. Moreover, Bekiros et al. (2020) indicated that the leptokurtic distribution of asset prices causes implicit herd behavior. Therefore, the same asset traded in different markets may exhibit different herd dynamics. This finding is important for Bitcoin spot and futures prices which have leptokurtic distributions and requires examination, not only in the center of the distribution but also in the left and the right tails.

Secondly, focusing on price discovery during the global Covid-19 pandemic can be justified by the significantly elevated risk levels present not only in financial markets, but also in cryptocurrency markets. To illustrate, Espinosa-Méndez and Arias (2021) show that herding behavior in Europe's capital markets has significantly increased during the global pandemic. Over the same period, the price of Bitcoin reached all-time highs, followed by sharp decreases, evidence of significant increases in volatility. Wang et al. (2021) analyzed the effects of positive feedback behavior in the Bitcoin market and found a significant and positive relationship between Bitcoin prices (and volumes) and trading behaviors during Covid-19. These results imply that the herding behavior of the Bitcoin market has significantly changed during the global pandemic. On the other hand, although Mnif et al. (2020) found an increase in cryptocurrency market efficiency during Covid-19, Kakinaka and Umeno (2021) concluded that the effect is more of a long-term effect, and herding behavior in the cryptocurrency market has increased in the short-term during the global pandemic. Similarly, King and Koutmos

(2021) found evidence in favor of heterogeneity in herding behavior for the cryptocurrency market. Therefore, it may be noteworthy to examine tail dependence between Bitcoin spot and futures markets during the global Covid-19 pandemic.

Finally, intraday data is utilized for this study, of which scant attention has been paid to regarding the price discovery process in Bitcoin spot and futures markets. Bouri et al. (2021) indicated that since intraday data exhibits different properties from daily closing price data, using intraday data for the Bitcoin market allows for the examination trading opportunities within the trading day. In addition, the sharp and rapid price changes in Bitcoin prices produce wilder fluctuations in these assets. According to the literature, high-frequency data becomes more useful in extreme noise platforms, better revealing the fear and greed response of investors to information arrivals. For instance, Blasco et al. (2011) stated that intraday data is more appropriate in investigating herd behavior. Similarly, Dobrev and Szerszen (2010) show that intraday data overcomes the underestimation problem of volatility during bearish states and the overestimation of risks during bullish states. Since intraday data allows news-based trading strategies, such data would enable a researcher to incorporate a great deal of price noise stemming from swift market developments. Since the Bitcoin market operates 24/7, it has become an ideal platform to measure the impact of the endless data stream caused by its independence of the trading hours for conventional securities. Thus, the data employed in this study has a high potential to capture event-based price developments in the Bitcoin market.

To preview our results, there is a bi-directional predictability between spot and futures markets under different market conditions. The feedback effect between Bitcoin spot and futures markets does not reveal which market figures prominently in terms of the price discovery process. On the other hand, the quantile impulse responses analysis shows the typical responses of the Bitcoin spot market to an unexpected extreme shock in the futures market is considerably higher than the responses of the Bitcoin futures market to an unexpected extreme shock in the spot market. These results suggest that while neither the futures market nor the spot market figures prominently in terms of price discovery, the Bitcoin futures market has an edge in terms of dominance over the spot market under various market conditions.

The rest of the paper is organized as follows: We provide a brief literature survey for the relation between spot and futures markets. We present the econometric methodology in Sect. 3 and empirical results are given in Sect. 4. We discuss the results in Sect. 5 and conclude in the final section.

2 Literature review

Theoretically, the arrival of new information affects asset prices both in spot and futures markets. Since in general futures markets have low transaction costs, are more liquid, and can process short positions, new information can be expected to have an instantaneous impact upon them. Fassas et al. (2020) contend there is ample evidence to support the hypothesis that price discovery is dominated by futures trading in a range of asset classes; e.g., in US equity markets, international equity markets, commodities, and foreign exchange markets. Indeed, the question which markets dominate price discovery is an unresolved debate (Patel et al., 2020). In the study on the relationship between spot and futures prices in commodity markets (corn, wheat, soybeans, soybean meal and oil, feeder, and live cattle) Dimpfl et al. (2017) find evidence that the prices of these commodities are almost uniquely formed in the spot market and the contribution of the futures contracts to price discovery is less than 10%. Jin et al.

(2018) examine the price discovery of Chinese gold spot and futures markets and concluded that the Chinese gold market's price discovery occurs predominantly in the futures market. Miao et al. (2017) investigate the price discovery process between the CSI 300 equity index and index futures in China. They find strong evidence that index futures dominate the price discovery. Yan and Guiyu (2019) examine price discovery of corn-starch cash and futures markets and found evidence that the futures price Granger causes the cash price. Xu (2018) investigates the cointegration relation and price discovery process for corn prices, finding that bi-directional information flows between spot and futures prices. Overall, the empirical literature generally shows futures markets come to the fore in the price discovery process. On the other hand, there is limited literature on Bitcoin futures markets as the market is still in its infancy.

The Chicago Mercantile Exchange (CME) and the Chicago Board Options Exchange (CBOE) launched the Bitcoin futures contract in mid-December 2017. Thereafter, work on the price discovery between Bitcoin futures markets and spot markets gained momentum (Alexander et al., 2019). Shortly after the introduction of Bitcoin futures, Bitcoin prices went into a serious decline. Hale et al. (2018) attribute this decline to pessimistic investors starting to actively trade in the Bitcoin market. The market, previously dominated by optimists, reversed course with pronounced participation by pessimists who wanted to take advantage of high prices and started short-selling. Hattori and Ishida (2020) find that in the long run the introduction of the futures market plays no part in the sharp decline in the spot price. They conclude that the introduction of Bitcoin futures did not crash the Bitcoin spot market at the end of 2017.

Asset pricing theory and experimental finance emphasize the moderating effects of futures contracts on asset price bubbles in spot markets, as there are more opportunities to take advantage of expected price changes (see Porter & Smith, 2003 for an early summary of evidence). Hence, Sebastião and Godinho (2020) state that the CBOE futures market is an effective instrument for daily hedging for Bitcoin and other cryptocurrencies such as Ethereum, Litecoin, and Ripple. However, there is no consistent evidence on the impact of Bitcoin futures contracts on the spot price of Bitcoin. Contrary to Hattori and Ishida (2020), Liu et al. (2020) find that the introduction of futures was responsible for the Bitcoin's price meltdown at the end of 2017. Using data from 7 major cryptocurrencies alongside Bitcoin, Liu et al. (2020) reports a meltdown of 26.50% in the price of Bitcoin in the first 45 days after the introduction of Bitcoin futures while positive returns continued for other cryptocurrencies. The study emphasizes a significant and negative relationship between the introduction of Bitcoin futures and Bitcoin returns while the relationship is either positive or insignificant for other cryptocurrencies. Kim et al., (2020) examine the effect of the Bitcoin futures market launch. Using data from 5 major cryptocurrency exchanges at different periods, bitFlyer (Japan), Coincheck (Japan), Bitstamp (E.U), Coinbase (U.S), and Binance (Hong Kong), they show that the Bitcoin market became unstable immediately after the launch of the futures market, but stabilized over time.

Köchling et al. (2019) examine the impact of the introduction of Bitcoin futures on cryptocurrency markets by focusing on weak-form efficiency. While weak-form efficiency for Bitcoin cannot be validated before the introduction of futures markets, the study finds evidence of weak-form efficiency with the introduction of futures markets and argues that Bitcoin prices became less predictable thanks to short selling and easier access by institutional investors to the cryptocurrency market. Similarly, Urquhart (2016) finds that the Bitcoin market was not efficient before the futures market, while Jiang et al., (2018) find evidence of long memory in Bitcoin prices. Brauneis and Mestel (2018) examine the efficiency of Bitcoin and 77 other cryptocurrency markets, concluding Bitcoin to be the least predictable.

Matsui and Gudgeon (2020) analyse the efficiency in futures markets and find that while 1-month Bitcoin futures prices were not efficient, 2-week and 1-week futures prices were. Accordingly, the market is more efficient with shorter contract lengths.

CBOE futures contracts were withdrawn in March 2019 and thus CME futures started to play a particularly strong price discovery role (Alexander & Heck, 2019). It can be expected that the trading of futures contracts of decentralized Bitcoin in an organized market will have the effect of reducing volatility in spot prices. Thus, the futures market will have a hedging function. However, Corbet et al. (2018) find the spot volatility has increased following the appearance of futures contracts in the Bitcoin market. The study also shows that price discovery is driven by uninformed investors in the spot market (97% of the information affecting Bitcoin prices). On the other hand, Fassas et al. (2020) examine the price discovery of Bitcoin spot and futures markets with evidence favouring a dominant role for the futures market in the price discovery process. Hu et al., (2020) find similar results using time-varying Granger predictability tests. Using BitMEX perpetual swap prices instead of CME and CBOE market data as future prices. In addition, Alexander et al. (2019) find that the BitMEX perpetual swap plays a dominant price discovery role.

Baur and Dimpfl (2019) argue that price discovery is led by the spot market. Accordingly, the spot market dominates price discovery because of the higher level of total trading volume in the spot market compared to futures markets, faster pricing of news in the spot market, and the ability to trade 24/7 in the spot markets. Matsui and Gudgeon (2020) find that the price of Bitcoin futures becomes a more accurate indicator of the spot price as futures contracts become shorter. Deng et al. (2021) examine the optimal trading strategy between Bitcoin spot and futures markets in terms of the Sharpe ratio and the Sortino ratio. They find that futures market may be used by investors when the volatility increases in the spot market to maximize their utility. Akyildirim et al., (2020) emphasize that spot market dominance in price discovery is driven by lower frequency data. They also stress that spot markets figured prominently early on when futures contracts were first launched; however, the situation was reversed with the entrance of sophisticated institutional investors. Other studies in the literature such as Karkkainen (2018), Kapar and Olmo (2019), Aleti and Mizrach (2020), and Hu et al. (2020) also conclude that the futures market figures prominently in the price discovery process.

The foregoing discussion implies there is no consensus in the literature on the price discovery process in the Bitcoin market. However, price discovery is about which market dominates prices when a financial instrument or a different financial instrument with a high correlation is traded in more than one market. Whether either market moves first is important for market participants and regulators (Kapar & Olmo, 2019). A summary of some extant studies in the literature with a focus on the price discovery process between Bitcoin spot and futures markets in terms of data source, market, data frequency, sample, and method are given in Table 1.

3 Econometric framework

In this study, two different econometric methods suggested by Candelon and Tokpavi (2016) and White et al. (2015) were used to better understand tail dependence between Bitcoin spot and futures markets. While the first method allows for the examination of tail dependence in terms of a multivariate Granger predictability framework, the latter can be used to investigate impulse responses under different market conditions.

Table 1 Literature review summary

Study	Spot market data	Futures market data	Data frequency	Sample period	Methods	Findings
Akyildirim et al. (2020)	Thomson Reuters Eikon	CME, CBOE	1, 5, 10, 15, 30, 60 min	December 18, 2017–February 26, 2018	IS, CS, IL, ILS	Futures prices dominate the price discovery process
Hu et al. (2020)	The Gemini auction and CME Bitcoin Reference Rate (BRR)	CME, CBOE	Daily	December 18, 2017–July 29, 2019	Time-varying Granger predictability and cointegration test, IS, GJS, DCC-GARCH-SNP model	Futures prices dominate the price discovery process
Fassas et al. (2020)	From Bitcoincharts.com	CME	Hourly	January 2, 2018–December 31, 2018	VECM, CFW, IS, CS, ILS, BEKK-GARCH, DCC-GARCH	Futures prices dominate the price discovery process
Aleti and Mizrach (2020)	Bitstamp, Coinbase, itBit, and Kraken	CME	Daily, 30 and 5 min	January 2, 2018–February 28, 2019	Cointegration, VECM, IS	Futures prices dominate the price discovery process
Alexander and Heck (2020)	The Gemini auction and CME Bitcoin Reference Rate (BRR)	CME, CBOE	30 and 1 min	December 18, 2017–June 30, 2019	VECM	Futures prices dominate the price discovery process

Table 1 (continued)

Study	Spot market data	Futures market data	Data frequency	Sample period	Methods	Findings
Alexander et al. (2019)	Bitstamp, Coinbase and Kraken	BitMEX perpetual Swap	Daily	July 1, 2016–January 3, 2019	VECM, MIS, CS, net spillover effect	Futures prices dominate the price discovery process
Baur and Dimpfl (2019)	Bitstamp	CME, CBOE	5 min	December 2017–October 2018	Cointegration, VECM, CS, IS, HIS	Spot prices dominate the price discovery process
Corbet et al. (2018)	Thomson Reuters Eikon	CME, CBOE	1 min	September 26, 2017–February 22, 2018	Information Share (IS), Component Share (CS), Information Leadership (IL), Information Leadership Share (ILS)	Spot prices dominate the price discovery process
Karrkainen (2018)	Coindesk Bitcoin Price Index	CBOE	1, 5, 15, 30, 60 min and 1 day	December 13, 2017–May 16, 2018	Johansen co-integration, Granger predictability, VECM, Information Share (IS) and Component Share (CS)	Futures prices dominate the price discovery process
Kapar and Olmo (2019)	Coindesk Bitcoin USD Price Index	CME	daily	December 12, 2017–May 16, 2018	The common factor component model and IS	Futures prices dominate the price discovery process

3.1 Predictability in distribution test

Candelon and Tokpavi (2016) suggest a new approach for ascertaining predictability in specific regions of the distribution of a series, such as the center or tails, and in doing so, they show that their method is a version of the Granger predictability test. Moreover, their method is advantageous compared to those that depend on copulas because the multivariate process of interquantile event variables can be examined.

The test statistic proposed by Candelon and Tokpavi (2016) is a multivariate version of the kernel-based nonparametric Granger predictability test suggested by Hong et al. (2009). The Granger predictability test in tail events suggested by Hong et al. (2009) is related to whether the lags of extreme downside risk from X_t can be used to predict an extreme downside risk of Y_t . Hong et al. (2009) define extreme downside events according to value-at-risk (VaR) at a specific risk level α , where the extreme downside risk is calculated as the losses in X_t and Y_t that are lower than VaR. In the Granger predictability-in-distribution test, a set of $A = \{\alpha_1, \dots, \alpha_{m+1}\}$ of $m + 1$ VaR risk levels cover the distribution support of both variables X_t and Y_t with $0 \leq \alpha_1 < \dots < \alpha_{m+1} \leq 100\%$. For the first time series X_t the corresponding VaRs at time t are $VaR_{t,s}^X(\theta_X^0, \alpha_s)$ $s = 1, \dots, m + 1$, with

$$VaR_{t,1}^X(\theta_X^0, \alpha_1) < \dots < VaR_{t,m+1}^X(\theta_X^0, \alpha_{m+1}) \tag{1}$$

where the vector θ_X^0 is the true unknown finite-dimensional parameter set related to the VaR model for X_t . If the distribution support of X_t is separated into m disjoint regions, each related to the indicator variable can be written as follows:

$$Z_{t,s}^X(\theta_X^0) = \begin{cases} 1 & \text{if } X_t \geq VaR_{t,s}^X(\theta_X^0, \alpha_s) \text{ and } X_t \leq VaR_{t,s+1}^X(\theta_X^0, \alpha_{s+1}) \\ 0 & \text{else} \end{cases} \tag{2}$$

where $s = 1, \dots, m$. For example, if we consider as $m + 1 = 5$, the set A is written as $A = \{\alpha_1, \alpha_2, \alpha_3, \alpha_4, \alpha_5\} = \{0\%, 20\%, 40\%, 60\%, 80\%\}$. Let $H_t^X(\theta_X^0)$ be vector $(m, 1)$ and components of the m event variables

$$H_t^X(\theta_X^0) = \left\{ Z_{t,1}^X(\theta_X^0), Z_{t,2}^X(\theta_X^0), \dots, Z_{t,m}^X(\theta_X^0) \right\}^T \tag{3}$$

One can define a second time series Y_t , with event variables in the vector $H_t^Y(\theta_Y^0)$ as:

$$H_t^Y(\theta_Y^0) = \left\{ Z_{t,1}^Y(\theta_Y^0), Z_{t,2}^Y(\theta_Y^0), \dots, Z_{t,m}^Y(\theta_Y^0) \right\}^T \tag{4}$$

The null hypothesis that Y_t does not predict X_t in distribution can be formulated as follows

$$\mathbb{H}_0 : E \left[H_t^X(\theta_X^0) \mathcal{F}_{t-1}^{X \& Y} \right] = E \left[H_t^X(\theta_X^0) \mathcal{F}_{t-1}^X \right] \tag{5}$$

Suppose $\hat{H}_t^X \equiv H_t^X(\hat{\theta}_X)$ and $\hat{H}_t^Y \equiv H_t^Y(\hat{\theta}_Y)$ are the estimated counterparts of the multivariate process of event variables $H_t^X(\theta_X^0)$ and $H_t^Y(\theta_Y^0)$ respectively and $\hat{\theta}_X$ and $\hat{\theta}_Y$ are \sqrt{T} consistent estimators of the true unknown parameter vectors θ_X^0 and θ_Y^0 . Let $\hat{\Lambda}(j)$ be the sample cross-covariance matrix between \hat{H}_t^X and \hat{H}_t^Y with

$$\hat{\Lambda}(j) \equiv \begin{cases} T^{-1} \sum_{t=1+j}^T (\hat{H}_t^X - \hat{\Pi}_X)(\hat{H}_{t-j}^Y - \hat{\Pi}_Y)^T & 0 \leq j \leq T - 1 \\ T^{-1} \sum_{t=1-j}^T (\hat{H}_{t+j}^X - \hat{\Pi}_X)(\hat{H}_t^Y - \hat{\Pi}_Y)^T & 1 - T \leq j \leq 0 \end{cases} \tag{6}$$

where the vector of $\hat{\Pi}_X$ (or $\hat{\Pi}_Y$) of length m is the sample mean of \hat{H}_t^X (or \hat{H}_t^Y). As in the case for univariate setting in Hong et al. (2009), one can replace $\hat{\Pi}_X$ and $\hat{\Pi}_Y$ by $\Pi_X = E(H_t^X(\theta_X^0))$ and $\Pi_Y = E(H_t^Y(\theta_Y^0))$, respectively. The sample cross-correlation matrix can be defined as:

$$\hat{R}(j) = D(\hat{\Sigma}_X)^{-1/2} \hat{\Lambda}(j) D(\hat{\Sigma}_Y)^{-1/2} \quad (7)$$

with $D(\cdot)$ being the diagonal form of a matrix and $\hat{\Sigma}_X$ and $\hat{\Sigma}_Y$ are the sample covariance matrices of \hat{H}_t^X and \hat{H}_t^Y . The test statistic can be expressed in weighted quadratic form that relates the current value of \hat{H}_t^X and the lagged values of \hat{H}_t^Y

$$\hat{T} = \sum_{j=1}^{T-1} \kappa^2\left(\frac{j}{M}\right) \hat{Q}(j) \quad (8)$$

where $\kappa(\cdot)$ is a kernel function, and M is the truncation parameter. The function $\hat{Q}(j)$ can be obtained by:

$$\hat{Q}(j) = T \text{vec}(\hat{R}(j))^T (\hat{\Gamma}_X^{-1} \otimes \hat{\Gamma}_Y^{-1}) \text{vec}(\hat{R}(j)) \quad (9)$$

where $\hat{\Gamma}_X$ and $\hat{\Gamma}_Y$ are the sample correlation matrices of \hat{H}_t^X and \hat{H}_t^Y respectively. The restrictions imposed on the truncation parameter M and the kernel function $\kappa(\cdot)$ are the same as in Hong et al. (2009). Candelon and Tokpavi (2016) define the test statistic as:

$$V_{Y \rightarrow X} = \frac{\hat{T} - m^2 C_T(M)}{(m^2 D_T(M))^{1/2}} \quad (10)$$

where $C_T(M)$ and $D_T(M)$ are:

$$C_T(M) = \sum_{j=1}^{T-1} (1 - j/T) \kappa^2(j/M) \quad (11)$$

$$D_T(M) = 2 \sum_{j=1}^{T-1} (1 - j/T)(1 - (j+1)/T) \kappa^4(j/M) \quad (12)$$

Candelon and Tokpavi (2016) showed that the test statistic has a standard Gaussian distribution under the null hypothesis and that it performs well in rejecting the null hypothesis of no predictability in case of linear and nonlinear predictability in the mean and in the variance using Monte Carlo simulations. The test also allows for the detection of asymmetry between the variables, as it also allows for distinguishing contagion or interdependence between financial markets. Interdependence suggests a long-run relation between the markets and it generally occurs in normal times based on the center of the distribution. On the other hand, contagion is the co-movement of the variables in extreme cases and is related to the tails of the distribution.

3.2 Quantile impulse responses analysis

White et al. (2015) suggest a multivariate regression quantile model that is labelled VAR for VaR model to examine tail dependence between the variables by impulse-response analysis. The multivariate quantile regression model depends on estimating the following multivariate

multi-quantile conditional autoregressive value at risk framework (MVMQ-CAViaR) which is a bivariate generalization of the CAViaR model suggested by Engle and Manganelli (2004):

$$q_{Y,t} = c_1(\theta) + a_{11}(\theta)|Y_{t-1}| + a_{12}(\theta)|X_{t-1}| + b_{11}(\theta)q_{Y,t-1} + b_{12}(\theta)q_{X,t-1} \tag{13}$$

$$q_{X,t} = c_2(\theta) + a_{21}(\theta)|Y_{t-1}| + a_{22}(\theta)|X_{t-1}| + b_{21}(\theta)q_{Y,t-1} + b_{22}(\theta)q_{X,t-1} \tag{14}$$

where θ is the risk level that varies between 0 and 1. Y_t and X_t are the spot and futures return series respectively and q_Y and q_X are the quantile functions at the risk level θ for spot and futures return series, respectively.

Equation (13) and (14) can be represented in matrix notation as follows:

$$q_t = c + A|Z_{t-1}| + Bq_{t-1} \tag{15}$$

such that q_t , Z_{t-1} , and c are vectors where $q_t = (q_Y, q_X)$, $Z_t = (Y_t, X_t)$, and $c = (c_1, c_2)$. A and B show the coefficients matrix for a_{ii} and b_{ii} that are defined in Eqs. (13) and (14). Equation (15) shows that quantiles of spot (futures) returns can be estimated by using its lag, lag of futures (spot) returns, lag of spot (futures) returns, and also lag of the quantiles of futures (spot) returns. In this context, while the diagonal elements of matrix B show the persistence of risk at a specified risk level, off-diagonal elements represent the risk spillover effects between Bitcoin spot and futures markets.

After estimating the MVMQ-CAViaR model, quantile impulse response functions (QIRF) can be conducted by using the estimated parameters from Eq. (15). Unlike standard impulse responses analysis, it is assumed that there is one intervention δ given to the observable Y_t only at time t ($\tilde{Y}_t := Y_t + \delta$) in the QIRF. The time-series behavior of Y_t with and without intervention can be represented as $\{\dots, Y_{t-2}, Y_{t-1}, Y_t, Y_{t+1}, Y_{t+2}, \dots\}$ and $\{\dots, Y_{t-2}, Y_{t-1}, \tilde{Y}_t, Y_{t+1}, Y_{t+2}, \dots\}$ respectively. Although this assumption is strict in the sense that it does not take into account the second moment of Y_t , it is essential to calculate an impulse responses function under the conditional quantile model.

White et al (2015) defined the pseudo QIRF for the first variable Z_{it} as follows:

$$\Delta_{i,s}(\tilde{Z}_{it}) = \tilde{q}_{i,t+s} - q_{i,t+s}, \quad s = 1, 2, 3, \dots \tag{16}$$

where $\tilde{q}_{i,t+s}$ is the conditional quantile of the affected series, and $q_{i,t+s}$ is the conditional quantile of unaffected series. The pseudo QIRF for the first variable (Y_t) can be presented as follows:

$$\Delta_{Y,1}(\tilde{Y}_t) = a_{11}(|\tilde{Y}_t| - |Y_t|) + a_{12}(|\tilde{X}_t| - |X_t|), \quad \text{for } s = 1 \tag{17}$$

$$\Delta_{Y,s}(\tilde{Y}_t) = b_{11}\Delta_{Y,s-1}(\tilde{Y}_t) + b_{12}\Delta_{X,s-1}(\tilde{Y}_t), \quad \text{for } s > 1 \tag{18}$$

For the second variable X_t , the QIRF can be represented as:

$$\Delta_{X,1}(\tilde{Y}_t) = a_{21}(|\tilde{Y}_t| - |Y_t|) + a_{22}(|\tilde{X}_t| - |X_t|), \quad \text{for } s = 1 \tag{19}$$

$$\Delta_{X,s}(\tilde{Y}_t) = b_{21}\Delta_{Y,s-1}(\tilde{Y}_t) + b_{22}\Delta_{X,s-1}(\tilde{Y}_t), \quad \text{for } s > 1 \tag{20}$$

We can define the QIRF as:

$$\Delta_s(\tilde{Y}_t) := \begin{bmatrix} \Delta_{Y,s}(\tilde{Y}_t) \\ \Delta_{X,s}(\tilde{Y}_t) \end{bmatrix} \tag{21}$$

If we define D_t as $\left| \tilde{Y}_t \right| - |Y_t|$, then the pseudo QIRF can be written as:

$$\Delta_s(\tilde{Y}_t) = AD_t, \quad \text{for } s = 1 \quad (22)$$

$$\Delta_s(\tilde{Y}_t) = B^{(s-1)}AD_t, \quad \text{for } s > 1 \quad (23)$$

The QIRF can be estimated using the processes above when there is an intervention to X_t . In order to orthogonalize the innovations, White et al. (2015) uses a standard Cholesky decomposition to identify the shocks.

4 Data and empirical results

In this study, the dynamic relation between spot and futures markets for Bitcoin is examined from January 12, 2020, through February 1st, 2021 using intraday (hourly) data, with a total number of 8,375 observations. Beginning at the start of the Covid-19 pandemic, the sample period contains episodes of record highs in the Bitcoin market. The study utilizes CME futures price for Bitcoin futures market, and the hourly data for the spot and futures markets (denominated in US dollars) is obtained from the Refinitiv Eikon database. The logarithmic return series is used for the empirical analysis.

The Candelon and Tokpavi (2016) predictability-in-distribution test depends on the estimation of time-varying VaR for each return series. Although there are several VaR estimation procedures in the literature, Füss et al. (2010) show that dynamic VaR models such as the CAViaR and the GARCH-type VaR generally outperform traditional VaRs. Similarly, Hung et al. (2008) and So and Yu (2006) find that GARCH class models estimate time-varying VaR reasonably well. Therefore, as in Candelon and Tokpavi (2016), this study utilizes GARCH class models in time-varying VaR for spot and futures return series.

Nevertheless, there is a well-documented literature on the adverse effects of outliers on GARCH models, specifically on GARCH parameters and conditional homoskedasticity tests (see Charles & Darné, 2005; Franses & van Dijk, 2011). Moreover, Grane and Veiga (2014) show that outliers significantly affect portfolio risk measures such as VaR, with distortions depending on the size of the outliers. These issues must be kept in mind when using the predictability- in-distribution test as they affect the estimation of VaR. Also, Ftiti et al. (2021) show that models which consider outliers provide a better fit in forecasting Bitcoin volatility. As such, we start the empirical analysis by first examining outliers within the return series. Although there are several outlier detection tests in the literature, the test suggested by Verardi and Vermandale (2018), which depends on calculating the box plot for the return series (and hence its simplicity), was utilized in this study. The test performs reasonably well for series that have skewed or heavy-tailed distributions. The latter is very important because the distribution of financial returns is generally leptokurtic. This outlier detection test resulted in 77 outliers in the futures return series and 88 outliers in the spot return series. As in Bodart and Candelon (2009) and Warshaw (2020), the return series is adjusted by considering outlier dates where each outlier is replaced by a 10-day average centered around the abnormal observation.

The descriptive statistics for the adjusted return series are presented in Table 2. The results show that the mean return for each series is positive during the Covid-19 period where the futures market provides a higher yield than the spot market. However, the volatility of the futures return series is also higher than the spot return series according to the estimated standard deviation. Although the futures return series exhibits strong positive skewness, the

Table 2 Descriptive statistics

	Spot	Futures
N	5227	5227
Mean	0.026	0.030
Median	0.020	0.000
Maximum	3.452	3.160
Minimum	− 3.060	− 4.156
SD	0.616	0.644
Skewness	− 0.039	0.195
Kurtosis	6.095	6.350
J-B	2,087.8 [0.000]	2,478.0 [0.000]
ARCH (5)	26.903 [0.000]	78.035 [0.000]
$Q(20)$	77.775 [0.000]	25.288 [0.190]
$Q_s(20)$	944.044 [0.000]	1,539.35 [0.000]
ADF	− 73.932***	− 70.826***
PP	− 73.961***	− 70.827***
KPSS	0.099***	0.070***

The numbers in square brackets show p -values of rejecting the null hypothesis. ARCH (5) suggests the LM conditional variance test. $Q(20)$ and $Q_s(20)$ give Box-Pierce serial correlation test statistics for return and squared return series, respectively. *** imply that the series in question is stationary at the 1% significance level

distribution of the spot return series has negative skewness. On the other hand, both return series have excess kurtosis which confirms both distributions are leptokurtic. The Jarque–Bera test strongly rejects the null hypothesis of normality for both return series. The Box–Pierce Q statistics show the autocorrelations in squared returns. Finally, unit root tests are used to ascertain whether all series are stationary in levels using Augmented Dickey–Fuller (ADF), Phillips–Perron (PP), and Kwiatkowski, Phillips, Schmidt, and Shin (KPSS) tests; the results strongly suggest stationarity for both series.

Next, a large class of GARCH models are considered, such as GARCH, EGARCH, GJR-GARCH, APARCH, FIGARCH, FIEGARCH, and FIAPARCH for estimating the time-varying VaR for returns. The model is then selected which best fits model information criteria such as the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). In the end, the EGARCH (1,1) model proposed by Nelson (1991) both for spot and futures return series was chosen, which is consistent with Bouri and Gupta (2021).

The model results presented in Table 3 show that the α and β parameters are significant at the 1% significance level. The estimated volatility parameters are similar in both models except for the leverage parameter. Although the estimated leverage parameter (γ) is negative for the futures returns, it is not statistically significant in either model. Furthermore, the persistence in volatility clustering parameter (β) is close to unity, which suggests high persistence in volatility.

Time-varying VaR is then calculated for each return series at different risk levels to examine the presence of tail dependence between spot and futures markets. Following Candelon and Tokpavi (2016), $A^L = \{0\%, 1\%, 5\%, 10\%\}$ and $A^R = \{90\%, 95\%, 99\%, 100\%\}$ for the left and right tail of the distribution respectively, where $m + 1$ equals 4. For the center of

Table 3 EGARCH class model results

	ω	α	β	γ	ν	ln(L)	$Q(20)$	$Q_s(20)$
Spot	-0.778 [0.065]	-0.646 [0.000]	0.996 [0.000]	0.002 [0.928]	3.295 [0.000]	- 4062.449	53.576 [0.000]	19.707 [0.349]
Futures	-0.733 [0.064]	-0.610 [0.000]	0.996 [0.000]	-0.003 [0.809]	3.447 [0.000]	- 4286.793	52.774 [0.000]	13.956 [0.731]

The numbers in square brackets show the p -values. ln(L) is the loglikelihood value. $Q(20)$ and $Q_s(20)$ give Box-Pierce serial correlation test values for the return and the squared return series, respectively. The EGARCH (1,1) model has the following volatility equation: $\log(h_t^2) = \omega + \beta(h_{t-1}^2) + \alpha\left(\left|\varepsilon_{t-1}/\sqrt{h_{t-1}^2}\right| - E\left|\varepsilon_{t-1}/\sqrt{h_{t-1}^2}\right|\right) + \gamma\left(\varepsilon_{t-1}/\sqrt{h_{t-1}^2}\right)$ where γ is the leverage parameter and ν is the student t distribution parameter.

Table 4 VaR Back-testing results

	Quantile (short positions)	Success rate	LR stat	Quantile (long positions)	Failure rate	LR stat
Spot	0.990	0.991	0.555 [0.456]	0.010	0.010	0.233 [0.628]
	0.975	0.975	0.056 [0.812]	0.025	0.028	2.260 [0.132]
	0.950	0.951	0.116 [0.733]	0.050	0.051	0.233 [0.628]
	0.990	0.988	1.726 [0.188]	0.010	0.009	0.362 [0.547]
Futures	0.975	0.971	2.011 [0.156]	0.025	0.021	2.279 [0.131]
	0.950	0.944	3.420 [0.064]	0.050	0.045	2.461 [0.116]

LR stat gives the Kupiec LR test results. The numbers in square brackets show the p -values

the distribution, the VaR risk levels are set as $A^C = \{20\%, 30\%, \dots, 70\%, 80\%\}$ where $m + 1$ is 7. In order to examine Granger predictability between spot and futures returns for ascertaining price discovery, the Bartlett kernel is used, and as in Candelon and Tokpavi (2016), the truncation parameter (M) is equal to 20 (corresponding to approximately one day).¹

The back-testing results for the VaR analysis are given in Table 4. Results indicate that the success rate in short positions and the failure rate in long positions are very close to the empirical quantiles, which suggests that the EGARCH model is adequate in gauging both upside and downside risks in returns. Kupiec's (1995) LR test result confirms this result as

¹ Candelon and Tokpavi (2016) calculated the truncation parameter via $[1.5T^{0.3}]$ where T is the number of total observations.

Table 5 Predictability in distribution test results

Predictability direction	Left tail	Right tail	Center
Spot → futures	59.975***	32.473***	18.829***
Futures → spot	114.857***	841.079***	23.047***

***Indicates a statistically significant Granger predictability at the 1% level

the null hypothesis cannot be rejected at conventional significance levels (such as 1% and 5%).²

After obtaining upside and downside risk events, Granger predictability tests are given in Table 5. In order to investigate risk spillovers or contagion effects between the two markets, the left tail of the distribution is examined. For example, finding bi-directional predictability between spot and futures markets in the left tail of the distribution suggests significant feedback during bad times, where unexpected losses in the spot market can be predicted by sudden past declines in the futures market or vice versa. Test statistics in Table 5 suggest a bi-directional price discovery process between spot and futures markets, where neither the spot market nor the futures market dominates the other in the Bitcoin price formation during bad times. On the other hand, the futures market seems to be one step ahead of the spot market in the price discovery process as the test statistics for predictability from the futures to spot returns are higher than the test statistics for predictability from spot to futures returns.

Similar results are observed for the right tail of the distribution: the statistics indicate bi-directional predictability between spot and futures markets at the 1% significance level. Results confirm there is a bi-directional price discovery between the spot and futures market during good times. As in the results for the left tail of the distribution, the test statistics for predictability from futures to spot returns are higher than the test statistics for predictability from spot to futures returns.

The test results for the center of distribution are similar with evidence of bi-directional predictability between spot and futures returns. Note that evidence of predictability in the center of distribution implies dynamic interactions between the two markets in normal times and hence it points to predictability-in-mean between the variables.³ Therefore, it can be said that there is a bi-directional price discovery process between spot and futures markets during normal times.

Overall, the predictability-in-distribution tests indicate a strong bi-directional predictability between Bitcoin spot and futures markets which seems to be robust over bearish as well as bullish markets. Investing in the Bitcoin spot market can seemingly hedge risk by using futures contracts over various market conditions.

Lütkepohl (2005) emphasized that Granger predictability test results are not adequate to understand the dynamic relationships among variables. This is important as the Granger predictability test results indicate bi-directional predictability between Bitcoin spot and futures markets and hence, additional evidence is needed to ascertain which market is dominant in the price discovery process. In order to gain an insight into the issue, impulse-response functions are utilized, which track the magnitude and the persistence of the responses of one

² We also use the Dynamic Quantile Test suggested by Engle and Manganelli (2004) and fail to reject the null hypothesis. The test results are available upon request.

³ We also employ predictability-in-mean and variance test suggested by Hong (2001) and find bidirectional Granger predictability between Bitcoin spot and futures markets both in-mean and variance. The test results are not reported to save space and are available upon request.

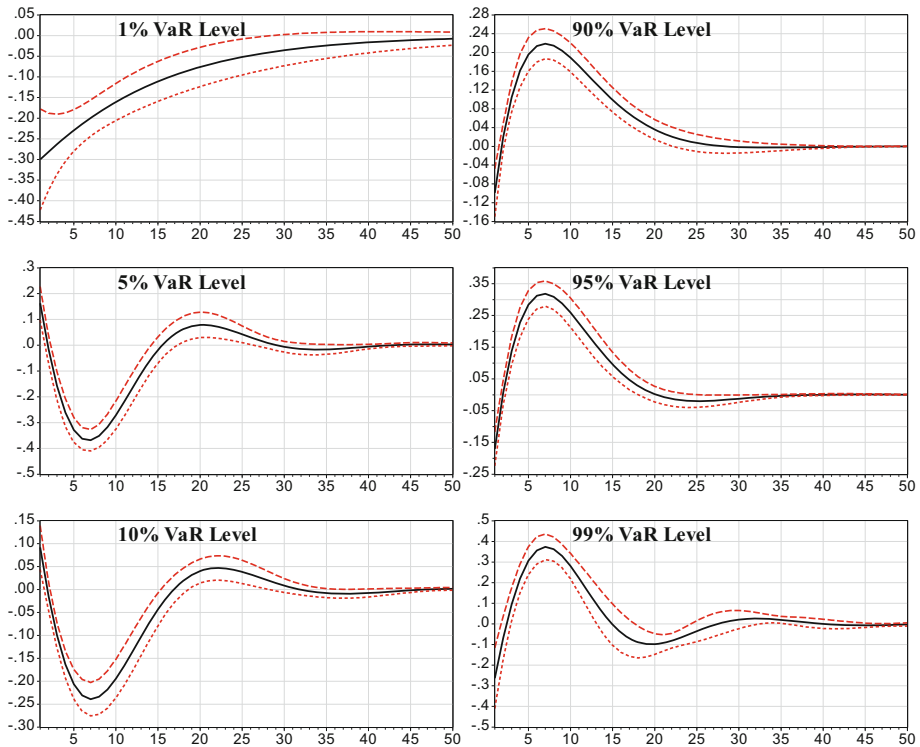


Fig. 1 Responses of the bitcoin spot market to a futures market shock. *Note* The dashed lines provide two standard deviation confidence intervals. The QIRF are calculated by using bivariate VAR for VaR model where the quantile of futures return series is estimated in the first equation and the quantile of spot return series is estimated in the second equation

market return to an unexpected shock to the return in another. For example, when comparing the responses of returns in one market to an unexpected shock in another market, the more pronounced response can be deemed less dominant in the price discovery process.

In order to estimate impulse responses, the bi-variate CAViaR model suggested by White et al. (2015) is first used, and then the quantiles for Bitcoin spot and futures returns at different risk levels are estimated.⁴ Three risk levels are considered for the left tail (1%, 5% and 10% level) and for the right tail (90%, 95% and 99%). Note that unlike standard impulse responses, the quantile impulse responses show the effects of extreme positive and negative shocks on returns at different risk levels. Results from quantile impulse responses, e.g., cumulative responses of spot returns to an unexpected two-standard-deviation shock in futures returns series are presented in Fig. 1.

The left panel of Fig. 1 shows cumulative responses of spot return series to unexpected shock in the futures return series for the left tail of the distribution. The right panel of Fig. 1 presents cumulative responses of the spot market to an unexpected positive shock in the future market. While the results in the left panel show downside losses in the spot market in response to an extreme loss in the futures market, the results in the right panel indicate upside gains in the spot market in response to an unexpected extreme gain in the futures market.

⁴ We do not present the bivariate CAViaR model results to save space; these are available upon request.

The cumulative responses of the spot market to an unexpected extreme negative shock in the futures market are negative and statistically significant up to the 25th lag at the 1% risk level. After the 30th lag, the responses start to die out and quickly converge to zero. On the other hand, the initial responses of the spot market to an unexpected negative shock in the futures market are positive at the 5% and 10% risk levels but turn to negative after the third lag. The reactions of the spot market are negative and statistically significant between the 4th and 15th lag. The results also show responses of the spot market die out after the 30th lag, converging to zero thereafter. The results suggest the impact of unexpected losses in the futures market on the losses in the spot market take almost a day and then the returns in the spot market converge to their mean under the ceteris paribus condition. Moreover, the maximum losses in the spot market in response to extreme unexpected losses in the futures market are 0.3%, 0.36%, and 0.32% at 1%, 5%, and 10% risk levels, respectively.

Results on the right panel in Fig. 1 show the initial responses of the spot market to an unexpected extreme gain in the futures market are negative and statistically significant at all three risk levels. Then, the responses turn positive after the third lag and remain positive and statistically significant up to the 20th lag. Thereafter, the responses converge to zero.

We present the cumulative responses of the futures market to an unexpected extreme shock in the spot market in Fig. 2. The left panel of Fig. 2 shows the results for downside losses

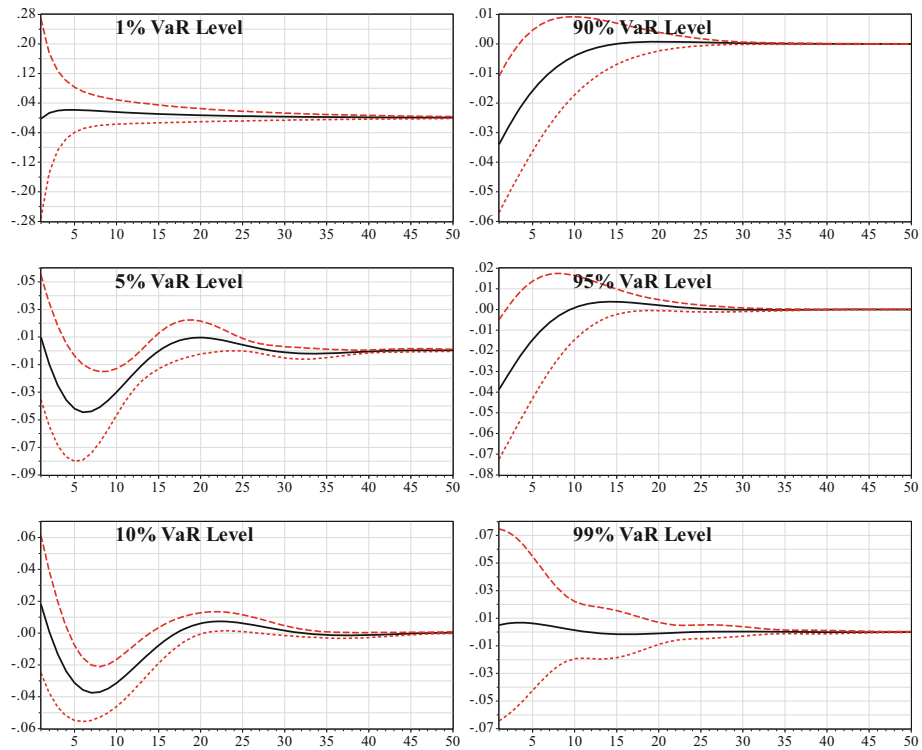


Fig. 2 Responses of the bitcoin futures market to a spot market shock. *Note* The dashed lines provide two standard deviation confidence intervals. The QIRF are calculated by using bivariate VAR for VaR model where the quantile of spot return series is estimated in the first equation and the quantile of futures return series is estimated in the second equation

at 1%, 5%, and 10% risk levels. At the 1% risk level, although the responses of the futures market to an extreme loss in the spot market are positive, they are not statistically significant. On the other hand, the initial responses of the futures market to unexpected extreme loss in the futures market are positive at 5% and 10% risk levels, but they turn negative and are only statistically significant between the 5th and 15th lags. The right panel of Fig. 2 shows that only the initial responses of the futures market to an unexpected extreme gain in the spot returns are negative and statistically significant at the 5% and 10% risk levels. In addition, responses of the futures market to an unexpected extreme gain are positive but not statistically significant at the 1% risk level. These results show the effect of the spot market on the futures market varies over risk levels, a point emphasized by Candelon and Tokpavi (2016). Accordingly, tests focusing only on a specific fixed level of the quantile may not be appropriate as time-series properties of the variables (such as nonstationary and long memory) may change in quantiles across the distribution. Moreover, Candelon and Tokpavi (2016) also suggested dynamic relations between variables may change at different risk levels, which is corroborated by impulse responses functions in Fig. 2; e.g., responses at 1% and 5% risk levels. Finally, the maximum losses in the futures market, given an extreme loss in the spot market are 0.002%, 0.044%, and 0.037% at the 1%, 5%, and 10% risk levels respectively.

Comparing the results in Figs. 1 and 2, it is evident that the responses of the Bitcoin spot market to an unexpected extreme shock in the futures market are considerably higher than the responses of Bitcoin futures market to an unexpected extreme shock in the spot market. This result suggests that the Bitcoin futures market has an edge in dominating the spot market. Evidence from the quantile impulse responses analysis show the futures market seems to be more dominant than spot market under various market conditions. These findings are consistent with results reported by Akyildirim et al. (2020), Hu et al. (2020), Fassas et al. (2020), Aleti and Mizrach (2020), Alexander and Heck (2020), Alexander et al. (2019), Karkkainen (2018), and Kapar and Olma (2019).

For robustness, cross-quantilogram analysis is employed as suggested by Han et al. (2016) in order to examine tail dependence between spot and futures markets. The cross-quantilogram depends on the calculation of the cross-correlations of the quantile-hit process obtained from quantile regressions suggested by Koenker and Basset (1978). We focus on left and right tail dependence between the variables and present the results in Fig. 3. Panel (a) of Fig. 3 shows predictability from spot to futures market. The left panel of Fig. 3 presents the left tail dependence between the spot and futures market. On the other hand, we show the right tail dependence between the series in the right panel of Fig. 3. Note that, while we use the 0.05 quantile level for spot and futures returns in calculating left tail dependence, the 0.95 quantile level is used for the right tail. The results in panel (a) of Fig. 3 show that the cross-correlations are positive and statistically significant at specific lags. This finding implies predictability from the spot market to the futures market both in the left and right tail. Similar results are found for predictability from futures to spot market as there are positive and significant cross-correlations in panel (b) of Fig. 3. These findings are consistent with the results in Table 5 and imply bi-directional predictability between Bitcoin spot and futures markets, which seems to be robust over bearish as well as bullish markets.

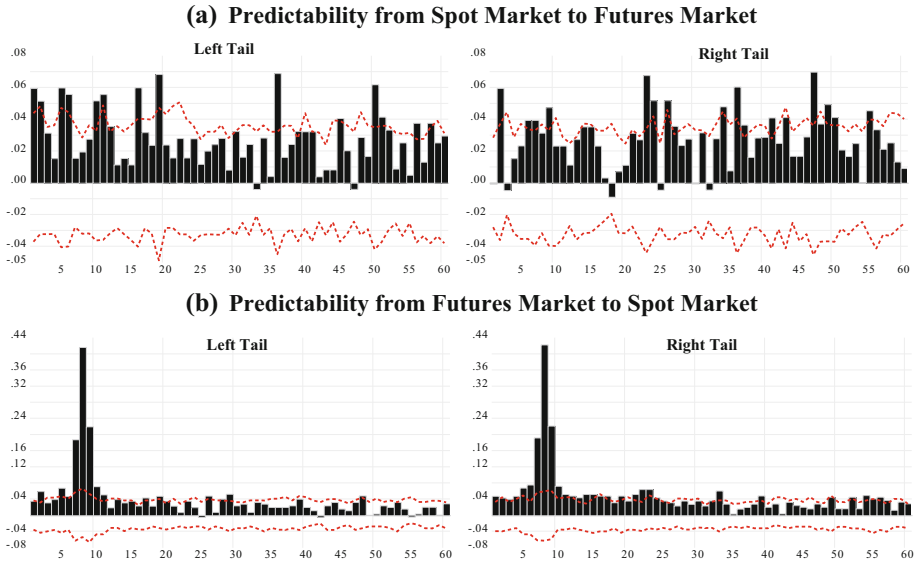


Fig. 3 The cross-quantilogram results. *Note* The dashed lines are two standard deviation confidence intervals obtained from stationary bootstrap with 1000 repetitions

5 Discussion

The presence of lead-lag relations between futures and spot markets for Bitcoin can be evaluated from different perspectives. For example, this study's empirical results may have implications for behavioral finance. Investor perception and behavior may differ depending on market conditions. This phenomenon is thoroughly examined in the finance literature (see Hanna et al., 2020; Hu et al., 2020; Chau et al., 2012; Zou & Sun, 2012). However, the evidence presented for investor sentiment and the spot/futures market interactions is quite limited. According to our empirical results, while the Granger predictability-in-distribution test and cross-quantilogram analysis results emphasized bi-directional predictability between Bitcoin spot and futures markets both in bearish and bullish market periods, the quantile impulse responses analysis results indicate the impact of spot prices on futures prices is limited in bullish market phases.

The bi-directional interactions in the left tail of the return distributions can be attributed to the co-movements of these two markets during market turmoil episodes. Such market phases contain sharp downward trends that are formed relatively faster than the upward developments. The panic in the market induces soaring fluctuations and it brings about asymmetric volatility meaning higher variability in declining markets. Our best-fitting model, the EGARCH model, suggests the presence of such asymmetry in the Bitcoin spot and futures market. The evidence regarding bidirectional volatility transmissions in the left tail of return distributions may shed light on possible causes of this outcome, besides asymmetric volatility. As reported by Peterson (2016), investor sentiment may become more significant and devastating on asset prices during bearish episodes. Similarly, Vidal-Tomás et al. (2019) find evidence of herd behavior during bearish markets in cryptocurrency markets. The authors attribute this outcome to the inefficiency and high volatility of the token market. Bikhchandani and Sharma (2000) report that herd behavior is a substantial factor in rising volatility and

exacerbating fragility in financial markets. Thus, it can be concluded that the aptness of the asymmetric volatility model to our dataset and significant mutual interactions in bearish phases can be attributed to the nature of investor anxiety observed in market crashes and the chaotic environment of turmoil.

When it comes to the right tail analysis, the quantile impulse responses analysis results suggest spillovers from futures to spot market are more pronounced. In this regard, it can be concluded that Bitcoin futures are superior to the spot prices concerning price discovery. The dominance of futures prices over the spot prices may indicate the order in disseminating and incorporating information arrivals, especially in upward market episodes. This outcome can be useful for traders who attempt to capture trend reversals in upward price markets and may reflect faster incorporation of information sets in the futures market than its spot market counterpart. However, the literature is replete with studies (see Al-Yahyaee et al., 2020; Vidal-Tomás et al., 2019; Caporale et al., 2018; Zhang et al., 2018) which suggest the cryptocurrency market is not a good candidate for the Efficient Market Hypothesis as far as reflecting information on asset prices in three different contexts. Considering this fact, one can surmise that the spillovers from the futures market to the spot market may be a spurious lead-lag relationship caused by herd behavior in the tokens market. Thaler (1991), Shefrin (2000), and Blasco et al. (2012) also point out that price adjustments might be due to the collective herd phenomena instead of the incorporation of information arrivals during market volatility.

As discussed in the literature, the cryptocurrency market is prone to display high and wild fluctuations (see Cheikh et al., 2020; Ammous, 2018; Fry and Cheah, 2016). However, the absence of evidence in volatility transmissions conditional on market states necessitates further analysis. The evidence revealed from three different market phases in the framework of return distributions within this study can be utilized to evaluate the effectiveness of hedging strategies in this market. Singhal and Biswal (2018) point out the importance of rebalancing the portfolio weights in the presence of switching market conditions. Likewise, Mensi et al. (2018) suggest holding less Bitcoin than other tokens during market turmoil. As our results illustrate, there exists a high and significant bi-directional predictability between Bitcoin futures and spot prices in bear markets. It can also be concluded that during the contractionary phase, the price discovery feature of the futures market might not work as effectively as in a bull market. Thus, the effectiveness of hedging may decrease during these periods. This outcome necessitates more meticulous risk management practices for Bitcoin investors during bearish markets when its futures are employed for hedging. In line with this suggestion, Ivanyuk (2021) shows that the dynamic adaptive portfolio management strategy utilized in crisis periods may significantly increase portfolio performance.

6 Conclusions

The introduction of futures markets by CBOE and CME for Bitcoin in December 2017 has prompted much academic research on its price discovery process. Using hourly data from January 12, 2020, through February 1st, 2021, this paper attempts to examine whether spot or futures markets lead in the price discovery process. Within this period, cryptocurrencies experienced record price highs in the face of the global Covid-19 pandemic. The significant contribution of this paper to the existing literature is its econometric methods, as this is, to the best of our knowledge, the first attempt to examine tail dependence between Bitcoin

spot and futures markets using predictability in the distribution test and the quantile impulse responses analysis.

We rely on tail dependence between Bitcoin spot and futures markets and use predictability in the distribution test and quantile impulse response analysis to better understand the dynamic relationship between Bitcoin spot and futures markets under a variety of market conditions. A variety of GARCH models are considered before the EGARCH (1,1) is selected, as it is the best fit for the model selection criteria by best characterizing both spot and futures returns. The back-testing results for the VaR analysis indicate the success rate in short positions and failure rate in long positions are very close to the empirical quantiles, which suggests the EGARCH model is adequate in gauging both upside and downside risks in returns.

Using time-varying VaR for each return series at different risk levels, tail dependence is examined between spot and futures markets. The Granger predictability test based on the left tail of the distribution shows bi-directional predictability between spot and futures markets, which suggests significant feedback effects following extreme losses. Unexpected losses in the spot market can be predicted by past losses in the futures market and vice versa. Repeating the tests for the right side of the distribution, similar results are obtained: unusually large gains in the spot market can be predicted by past gains in the futures market and vice versa. Statistics from the center of the distribution tell the same story where we find bi-directional Granger predictability and neither the spot market nor the futures market dominates the other in the Bitcoin price formation during normal times.

The CAViAR framework is then used along with the associated impulse response functions that provide an estimate of dynamic tail dependence to gain insights into the spillovers between quantiles of spot and futures returns. Impulse response functions are estimated at various risk levels for a given loss or gain in a market and measure the dynamic response of returns in the other market. The cumulative responses of the spot market to an unexpected extreme negative shock in the futures market are negative and statistically significant within a day. The same is also true for responses of the spot returns to unexpected extreme gains in the futures market where such responses are negative and statistically significant at all three risk levels. Turning to the responses of the futures market to extreme losses or gains in the spot market, they tend to be smaller, initially marginally significant, or not significant at all. Overall, the futures market has an edge in influencing the spot market and figures more prominently in the price discovery process.

Our empirical findings can be useful for investors and firms that take positions in both the spot and futures markets of Bitcoin. As the results indicate, interactions of these two markets display varying behavior under different market conditions. This information emphasizes the importance of dynamic portfolio management in such volatile markets. Although the introduction of Bitcoin futures allows the market participants to mitigate the extent of risk exposure, varying reactions of these variables under different market conditions necessitate a rigorous follow-up and time-adaptive procedure to determine hedge ratios. Results reveal that disseminated market information is incorporated in either variable with an erratic pattern under different confidence levels and signs of returns. Therefore, it can be concluded that the performance of long or short hedges might be dissimilar due to the varying extent of reactions of both markets to the same degree of shocks. As our methodology allows us to distinguish the interactions between spot and futures prices in bearish and bullish markets, we are also able to evaluate the respective relationship from the perspective of these two market phases. Accordingly, we conclude that upward and downward market trends reveal different behaviors of investor sentiment in the cryptocurrency market. Although quantile impulse responses analysis depicts a limited impact of spot prices on futures in downward

market phases, distribution test and cross-quantilegram analysis illustrate the presence of bi-directional predictability in these market phases. Considering the advantage of evidence from two different perspectives in the latter, this observation indicates that during the panic environment of the downward trends, the co-movements of spot and futures prices strengthen. In their nature, such markets display severe fluctuations and may incorporate asymmetric volatilities that suggest the existence of higher fluctuations in declining prices, as suggested by our findings in the EGARCH model. The presence of bi-directional predictability during the high market tension depicts diminishing price discovery of the futures and spot markets. Thus, we suggest utilizing alternative hedging instruments that can be used during the market turmoil in portfolios constructed with Bitcoin. However, as the results for right tail analysis depict, futures are more pronounced in leading the spot prices during upward market trends. In such market phases, investors may benefit from the lead-lag relationship between futures and spot prices since the market information arrivals would follow a sequence and the incorporation of information will have an order. The leading characteristic of futures on spot prices in bullish trends may offer more efficient hedging and trading strategies for investors and portfolio managers. On the other hand, we suggest seeking alternative hedging instruments for any investor with a long position in spot Bitcoin by considering the diminished price discovery feature between spot and futures prices during the downward market trends.

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