



Does Price Discovery Process Hold during Post-COVID Period in Cryptocurrency? Evidence from Bitcoin

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Received: 17 April 2025

Accepted: 10 August 2025

DOI: <https://doi.org/10.32479/ijefi.20427>

ABSTRACT

With the introduction of derivatives contracts in the market, it is expected that these instruments will assist the markets with price discovery mechanism. The price discovery mechanism enables the spot market to assess the future expectations of the market by assessing the trends in the prices of futures contracts of underlying securities. Since the inception of derivative contracts on bitcoin in 2017, the derivative market has witnessed significant surge in overall trading volumes and turnover. With more contracts being traded in bitcoin futures, it becomes imperative to assess whether this is leading to price discovery process or not. The world has also witnessed the COVID-19 as black swan event in past few years and it is equally important to assess whether there is any impact of COVID-19 on the price discovery process in bitcoin market. In view of this, the present study tries to assess the impact of COVID-19 on price discovery process on bitcoin. The study considers the daily time series data of bitcoin and bitcoin future from 2017 to 2024 and applies standard time series econometrics methods including test of stationarity, Johansen co-integration test, vector error correction mechanism and Wald test to assess the long-run and short-run causality between bitcoin spot and future contracts. The results of the study suggest that price discovery is taking place in bitcoin market and Covid-19 has no significant impact on the price discovery process in bitcoin.

Keywords: Bitcoin, Price Discovery, Lead-Lag Relationship, Causality, VECM, Co-integration

JEL Classifications: C01, C22, D53, G13, G14

1. INTRODUCTION

The cryptocurrency sector, led by Bitcoin, has grown exponentially in investor interest and trading activity over the past decade. Bitcoin is the first and largest digital currency by market value and trade volume, making it important to the global financial system. In February 2021, its market value topped \$1 trillion, indicating its growing popularity as a speculative investment and store of value (Statista, 2021). Decentralization, borderless transferability, and reduced intermediary dependence have made cryptocurrencies popular, especially among retail investors. Price discovery—the process by which market prices react to new information—is crucial to understanding market efficiency and information flow. Effective price discovery is

essential for investor confidence, market transparency, and financial system functioning. Fama's (1970) Efficient Market Hypothesis states that asset prices should immediately reflect all publicly available information. This ideal is typically deviated from by transaction costs, liquidity limits, and trading system variances (Fleming et al., 1996; Kumar et al., 2017; Sharma et al., 2024).

Bitcoin futures were offered on major regulated exchanges CBOE and CME on December 10 and 17, 2017, respectively. These developments constituted a major step toward Bitcoin's financial ecosystem integration. Futures markets, with reduced transaction costs and more liquidity, should lead spot markets in price discovery (Silber, 1981). Price discovery in the Bitcoin market

has been corroborated by empirical studies like Sharma et al. (2022) showing that Bitcoin futures drive spot market movements. This leads to the study's first research question: Is Bitcoin price discovery happening?

While price discovery in the cryptocurrency market is under study (Sharma et al., 2022), the COVID-19 epidemic caused unprecedented financial market uncertainty and volatility (Olasiuk et al., 2023; Olasiuk et al., 2025). Bitcoin, a hedging or speculative asset, fluctuated rapidly due to investor sentiment and global economic disturbances. Understanding how a significant external shock influenced price discovery efficiency and direction is crucial. This raises the second research question: RQ2: How has the COVID-19 outbreak affected Bitcoin price discovery?

The study explores the lead-lag relationship between Bitcoin spot and futures prices in three phases: pre-COVID, post-COVID, and the whole sample. This segmentation lets price discovery behavior be compared across structurally varied market situations. The study of currency derivatives in India by Sharma and Chotia (2019) shows how price discovery effectiveness can vary greatly between timeframes and economic settings. Sharma et al. (2020) show how geopolitical and regional differences affect BRICS price discovery, providing methodological insights for temporally segmented analysis. RQ3, the final research question, is informed by these findings: Do price discovery behaviours differ pre- and post-COVID? Sharma et al. (2023) also evaluate price discovery literature, highlighting trends and research gaps in derivative and digital asset markets. This paper extends empirical price discovery methodology to turbulent and fast changing Bitcoin futures and spot trading during the pandemic. The study examines time-series correlations and causality patterns across phases to understand how a big global event like COVID-19 affected Bitcoin price discovery efficiency and direction.

2. REVIEW OF RELATED LITERATURE

In any economy, discovery of price along with hedging are the two main purposes of futures contracts on securities. As per the functional equation of price discovery, underlying assets prices should incorporate the expectations of market participants for future prices, which are reflected in the prices of futures. Therefore, it is anticipated that futures prices will drive spot market activity, serving as a sort of prelude to these exchanges (Silber, 1981; Sharma et al. 2023).

Futures markets are frequently used as leading indicators for spot market indices, according to numerous research that have looked at this link for various financial assets. For instance, Cornell and French (1983) compared the efficiency of price of equity futures in the US by making a comparative study of spot and futures prices against the S&P 500. Similarly, Kawaller et al. (1987) utilised the data very minutely ranging for every minute for S&P 500 to empirically support this link. While Nhung et al. (2019) verified price discovery in Vietnam using VN 30 Index data. Rajput et al. (2012) investigated discovery of price in India using S&P CNX daily data. Furthermore, futures contracts prices in the futures

contract market amongst BRICS countries was confirmed by Sharma et al. (2020).

Commodity markets have been found to follow similar principles. While Yang et al. (2001) studied pricing efficiency for both types of commodities whether it is storable or not and established a comparison that on an usual basis spot prices are led by futures prices with little influence from storage conditions, Beck (1994) examined price discovery across eight commodities. Mahalik et al. (2010) verified the effectiveness of pricing in the futures of commodity market in India, while Shrestha (2014) reaffirmed the presence of price discovery mechanism in the energy industry. Price discovery in metals, energy, and agricultural commodities was further investigated in studies by Dimpfl et al. (2017) and Chinn and Coibion (2014).

Price discovery mechanism across currencies of different countries and their markets has been of interest in earlier studies. Chen and Gau (2010) investigated the relationship between different currencies ranging from USD to JPY to EUR among their both spot and futures prices and found that they were impacted by macroeconomic news announcements. They discovered that spot pricing trailed futures prices. Osler et al. (2011) proposed a two-tier price discovery mechanism after studying price discovery across the currencies market while taking interdealers' and clients' roles into account.

Rosenberg and Traub (2009) focused on US dollar futures and spot prices on the Chicago Mercantile Exchange. Kumar (2018) analyzed USD futures and spot prices for INR, BRL and ZAR. Sharma and Chotia (2019) examined the same things for Indian context. These studies consistently demonstrated that spot prices were led by future prices for various underlying assets, including equities, commodities, and currencies. They also confirmed a long-term causal correlation between spot and futures prices across the asset classes.

The main areas of research on cryptocurrencies have been assessing the risk-return characteristics of these assets (Bariviera, 2017), predicting the time-series returns as an efficient method in spot market (Brauneis and Mestel, 2018), analysing trends which are predictable within cryptocurrency markets (Phillip et al., 2018), and looking at how information is shared across various cryptocurrencies (Qureshi et al., 2020). Although several studies have looked at how futures prices might forecast spot prices in cryptocurrency markets, they haven't used prolonged daily time series data to look at the causal relationship under a long-term period between both bitcoin's spot and futures and prices. Baur and Dimpfl (2018) investigated this relationship using high-frequency data until October 18, 2019, focusing on trading volume and hours for both spot and futures bitcoin prices. Their results showed a reverse causal relationship, with futures prices trailing behind spot prices, which acted as a leading indication for futures.

Bitcoin price discovery in uncontrolled markets was examined in a 2020 study by Alexander and Hecky using multi-dimensional, minute-level data analysis. According to their findings, there was a causal relationship amidst spot and future prices covering these

unregulated exchanges, with futures prices outperforming spot prices. Moreover, Alexander et al. (2020) discovered that BitMEX, a trading platform using crypto currency, is a leading predictor of cryptocurrency market price and volume fluctuations. They also found that their results were sensitive to temporal factors, including “day-of-week” and “time-of-day” effects. The recent studies by Sharma et al. (2024); and Sharma et al. (2025) has also suggested effect of ESG on the price discovery process under different markets and sectors.

Karkkainen (2018) used the data between December 13th, 2017 and May 16th, 2018 to look upon the price discovery mechanism in the bitcoin market and comparing the prices futures and spot market. This study was conducted when markets were in their early phases of futures trading. An impact in the spot prices of bitcoin futures contracts was indicted by his study following their launch on the CBOE and then the CME. These results were vetted by studying the daily data during the same period. Hence the role an experienced trader was established as a leading indicator for spot prices in the bitcoin futures market. In synchronous to this, Kapar and Olmo (2019) examined the bitcoin’s-based price discovery during this period using daily time-series data. Their analysis revealed shared characteristics influencing both futures and spot prices, indicating an equilibrium in price discovery was more applicable to evaluating prices in the spot market converging bitcoin market than prices in futures market.

Fassas (2021) assessed the mechanism of price discovery, identified the process LIBOR rates and Secured Overnight Financing Rates (SOFR). Venter and Maré completed their research in 2022 and showcase that when VIX was added to a GARCH model, this leads to good results as estimates by using a Student’s t-distribution. Through the examination of its role in identifying overall mechanism process in the spot market, primary models helps a lot in calculating and evaluating an equation of price discovery i.e. Component sharing (CS) (Booth et al., 1999; Harris et al., 2002), and information share (IS) (Hasbrouck, 1995). Research has demonstrated that for each market the level of noise in terms of volatility in the market affects the CS and IS models (Fassas, 2021).

Fassas et al. (2020) reviewed data for a period ranging from 2nd of January to 31st of December for the year 2018 and came out with the fact that new coverage of information in the bitcoin market impacts first of all prices of futures, then spot prices. The study also discovered a causal relationship between prices in spot market and futures of bitcoin which is two-way.

Dynamics of price variation between spot and futures prices of Bitcoin were investigated making use of high-frequency data by Akyildirim et al. (2020). According to their analysis, spot prices are frequently surpassed by Bitcoin futures prices, suggesting a price leadership connection. The analysis also discovered that futures of Bitcoin posted on the CBOE have been far more efficient than those published on CME exchange. Overall, comparatively small sample sizes limit the body of research on price discovery covering impacts on the markets of bitcoin.

3. METHODOLOGY

The current research uses Bitcoin as a case study, focusing on the analysis of its futures and spot prices. The study utilizes daily time series data for Bitcoin’s spot and futures closing prices, spanning from February 23, 2017 to September 30, 2024. The data was obtained from the financial repository “Investing.com.” After extracting the data, it was cleaned to remove null values and adjusted to align the prices on corresponding dates across the two data series. After this we have used common statistical techniques for analysis of time series data were used to evaluate the price discovery process in Bitcoin.

3.1. Test for Stationarity

To test the stationarity in our dataset of Bitcoin’s spot prices and Bitcoin’s Future prices we deployed the Augmented Dickey-Fuller (ADF) Test (Dickey & Fuller, 1981) to find out whether the time series variable is stationary or not stationary. The tests were developed by Dickey and Fuller and Phillips and Perron respectively. If the data series is stationary which means it will not change its statistical properties over time. The ADF test includes the extra step of lagged differences of the timeseries in the basic Dickey Fuller test to find out the more complex patterns in the data. The PP test tries to fix the problem of patterns in the error in the data. In both the tests, the null hypothesis is that the timeseries is nonstationary. If the test statistic value is less than the critical value, then we will reject the null hypothesis making the timeseries as stationary.

3.2. Test for Causality

To find out the integration order of the two timeseries variables we have used the co integration test of Johansen and Juselius Johansen and Juselius (1990). And the Vector Error Correction Mechanism (VECM) developed by Hasbrouck was used to find the long-term causal relationship in the two variables. The VECM test is used to understand the complex patterns and relations in the timeseries variables and long-term equilibrium between the co-integrated variables.

The VECM model is calculated using the following equations:

1. $\Delta(\text{Bitcoin Spot}) = \alpha_1 + \Sigma(\beta_{1i} \Delta(\text{Bitcoin Spot})_{t-i}) + \Sigma(\gamma_{1i} \Delta(\text{Bitcoin Futures})_{t-i}) + \lambda_1 \text{ECT}_{t-1} + \varepsilon_{1t}$
2. $\Delta(\text{Bitcoin Futures}) = \alpha_2 + \Sigma(\beta_{2i} \Delta(\text{Bitcoin Futures})_{t-i}) + \Sigma(\gamma_{2i} \Delta(\text{Bitcoin Spot})_{t-i}) + \lambda_2 \text{ECT}_{t-1} + \varepsilon_{2t}$

In the above equations, Δ denotes the differencing of first order for both the time series variables and the ECT represents the lagged error correction term. The coefficient β tells us about the speed at which the variables adjust to restore equilibrium and γ tells us about the short-term adjustment changes. The significance and sign of the error correction term (ECT) are very crucial. If the ECT is significant and has negative sign tells us that the long-run causality between the two time series variables. To select the optimized lag length for VECM, the study uses the VAR framework, selecting the number of lags is decided through the lowest values of Akaike Information Criteria (AIC) and Schwarz Information Criterion (SIC). This model ensures that the model is capturing the changes in the data effectively.

4. RESULTS AND DISCUSSION

The data is divided into two parts: from February 23, 2017 to March 25, 2020 and from March 25, 2020 to September 30, 2024. This segmentation provides us way for analysis of the impact of the COVID-19 on the price discovery process of Bitcoin from Bitcoin Futures by comparing the periods of before pandemic and after pandemic.

The Augmented Dickey-Fuller (ADF) unit root test assessed Bitcoin spot and futures price series stationarity. Tables 1 and 2 details the outcomes. For the Bitcoin spot price, the ADF test at level produced 0.439 with a $P=0.159$, showing a unit root and non-stationarity. At the first difference, the ADF test statistic was -33.406 with a $P=0.000$. These results significantly reject the unit root null hypothesis, demonstrating that Bitcoin spot price series becomes stationary after differencing at first. The ADF test at level for Bitcoin futures price showed non-stationarity with a test statistic of 0.389 and a $P=0.028$. After initial differencing, the ADF test statistic was -33.806 with a $P=0.000$. Finally, the ADF test consistently reveal that Bitcoin spot and futures price series are non-stationary at levels but stationary after differencing. This indicates that both series are integrated of order one, $I(1)$, which is necessary for time-series analysis like Johansen cointegration and Vector Error Correction Model (VECM) to study price discovery dynamics between the two markets.

During pre-COVID period, The ADF test at level for Bitcoin spot price showed a unit root and non-stationarity with a test statistic of -0.376 and a $P=0.641$. The ADF test statistic was -19.979 with a $P=0.000$. For the Bitcoin futures price, the ADF test at level showed -0.915 with a $P=0.473$ showing non-stationarity. AT the first difference, the ADF statistic was -20.061 with a $P=0.000$ indicating that the series becomes stationary. These results show that Bitcoin spot and futures price series were non-stationary at their levels before the pandemic but became stationary after initial differencing, meaning that they were integrated of order one, $I(1)$.

During post-covid, ADF test at level yielded 0.375 with a $P=0.262$ for the Bitcoin spot prices. However, after initial differencing, the ADF test provided -26.262 with a $P=0.000$ suggesting stationarity. ADF test at level provided 0.387 with a $P=0.053$ for Bitcoin futures price suggesting non-stationarity. After initial differencing, the ADF test statistic was -26.656 with a $P=0.000$ confirming the series' stationary status. Thus, post-COVID, Bitcoin spot

and futures price series are non-stationary at levels but become stationary after differencing, confirming their integration of order one, $I(1)$.

The results of the Johansen cointegration test (Table 3) suggest the long-term cointegration relationship between Bitcoin Spot and Bitcoin Future. The test statistic of the null hypothesis for Bitcoin Spot and Bitcoin Futures is more than the critical value of the test at the 5% level of significance, showcasing the confirming of long-term relationships between the time series variables. This shows us that the Bitcoin spot and Bitcoin futures have long-term relationships with showing the short-term fluctuations. The similar observations are made in pre-COVID and post-COVID data splits. This further confirms that there is long-term cointegrating relationship between bitcoin spot and bitcoin future during pre- and post-COVID period and aggregate data.

The Error Correction Model (ECM) estimation results (reported in Table 4) give key insights into the long-run causal link between Bitcoin futures and spot prices over the complete sample, pre-COVID, and post-COVID eras. The post-COVID coefficient of the error correction term (ECT) in the spot price equation is -2.029 , which is statistically significant. The negative and substantial coefficient suggests a strong long-term causation between Bitcoin futures prices and spot prices post-pandemic. The relatively large coefficient reflects a speedier adjustment toward the long-run equilibrium in the context of short-run disequilibria, highlighting the futures market's growing dominance and informational leadership in price discovery. Before COVID, the ECT coefficient was 0.750, which is positive and statistically insignificant. This implies no long-run equilibrium relationship and no causality from Bitcoin futures to spot prices before the outbreak. The negligible coefficient shows that spot market price adjustments were not influenced by variations from a consistent long-term link with futures prices. In full-sample analysis, the ECT coefficient is -0.402 , which is negative but not statistically significant. In the overall sample, there is no strong evidence of long-term causality from futures to spot prices, presumably due to structural changes or regime shifts caused by the COVID-19 outbreak, which dilute the long-term link. No long-term association is found between spot and futures prices across any of the three timeframes. In pre-COVID, post-COVID, and full-sample periods, Bitcoin spot prices do not affect futures prices long-term since the futures equations' ECT coefficients are positive or statistically negligible. These findings show that post-COVID price discovery became more futures-led,

Table 1: Test of Stationarity of Bitcoin spot prices

Test Level	Pre-Covid		Post-Covid		Full Sample	
	ADF test	P-value	ADF test	P-value	ADF test	P-value
At Level	-0.376	0.641	0.375	0.262	0.439	0.159
At 1 st difference	-19.979	0.000	-26.262	0.000	-33.406	0.000

Table 2: Test of stationarity of bitcoin future prices

Test Level	Pre-COVID		Post-COVID		Full sample	
	ADF test	P-value	ADF test	P-value	ADF test	P-value
At level	-0.915	0.473	0.387	0.525	0.389	0.285
At 1 st difference	-20.061	0.000	-26.656	0.000	-33.806	0.000

Table 3: Trace statistics

Test Level	Null	Eigen value	Test statistic	0.05 Critical value
Aggregate data	None ($r=0$)	0.1997843	510.38	15.67
	At most 1 ($r\leq 1$)	0.1329363	326.65	9.24
Pre-COVID	None ($r=0$)	0.1710463	163.20	15.67
	At most 1 ($r\leq 1$)	0.1001626	91.82	9.24
Post-COVID	None ($r=0$)	0.2945121	491.55	15.67
	At most 1 ($r\leq 1$)	0.1360848	206.11	9.24

Table 4: Error correction mechanism

Test Level	Future to Spot		Spot to Future	
	CointEq1	Standard Error	CointEq1	Standard Error
Before COVID	0.75	(0.1025)***	1.8076	(0.1442)***
After COVID	-2.0286	(0.7481)**	3.7474	(0.7194)***
Full sample	-0.4020	-0.2775	2.387	(0.2760)***

reflecting a shift in market dynamics possibly caused by increasing institutional participation, market maturity, or pandemic volatility. The absence of long-run causation in pre-COVID and full-sample periods shows how Bitcoin futures markets have changed spot price behavior.

4.1. Findings

The empirical analysis demonstrates that Bitcoin price discovery occurs, answering RQ1: Is price discovery taking place? VECM shows substantial short-run dynamics between Bitcoin futures and spot prices. Both markets adjust prices to a long-run equilibrium, showing active price discovery. Bitcoin futures prices reflect fresh market information before spot prices, showing that futures markets shape Bitcoin's price. As for the first research question, RQ2: How has the COVID-19 pandemic affected Bitcoin price discovery? it has had a major impact. Post-COVID, the ECT coefficient is negative and significant (-2.029), indicating a faster and stronger adjustment towards long-term equilibrium between futures and spot prices. In contrast, the pre-COVID ECT is positive and negligible, indicating no long-term causality. A structural shift during the epidemic strengthened the futures market's dominance in price discovery and market efficiency and responsiveness to new information. The first research question, RQ3, is: Does price discovery behaviour alter pre- and post-COVID? The study suggests that pre- and post-COVID price discovery behaviour differs significantly. No significant long-run causality from futures to spot prices was detected before the pandemic, suggesting weaker or absent futures market price discovery leadership. In contrast, post-COVID, futures to spot prices show strong and significant long-run causation, indicating that the futures market led price movements. This shows how the pandemic changed market dynamics, presumably due to increased institutional participation and volatility that improved futures market informational efficiency.

5. CONCLUSIONS AND IMPLICATIONS

This study explored Bitcoin price discovery by studying dynamic interactions between Bitcoin futures and spot prices

pre-COVID, post-COVID, and the whole sample. In the post-pandemic period, Bitcoin futures are crucial to price discovery. A Vector Error Correction Model is justified because spot and futures prices are non-stationary at levels but become stationary after differencing. Importantly, the long-run causation from Bitcoin futures to spot prices is only substantial post-COVID, showing a market shift likely caused by the pandemic. This shows that the futures market is more efficient and effective at reflecting new information, influencing spot prices more. Long-term causation is absent in the pre-COVID period, and the entire sample data, which mix these periods, hide this dynamic. The absence of considerable causation from spot to futures prices during all periods supports the unidirectional price discovery process, with futures prices leading. The study found that the COVID-19 pandemic has increased Bitcoin futures markets' price discovery function, maturing and improving cryptocurrency markets. This work has practical and theoretical implications:

For traders and investors: Investors and traders can enhance timing and execution by understanding that Bitcoin futures prices lead spot prices, especially post-pandemic. Futures markets provide early price signals for better trading and risk management.

Market regulators/policymakers: Futures markets are more important in price discovery, highlighting the necessity for comprehensive cryptocurrency derivatives regulation. Futures trading clarity, liquidity, and market integrity can stabilize Bitcoin and safeguard investors.

For Researchers: This work documents price discovery techniques before and after a severe exogenous shock, adding to bitcoin market dynamics literature. These conclusions can be expanded by studying other market efficiency parameters and other cryptocurrencies and derivative instruments.

For Market Infrastructure Providers: Futures' increased importance in price discovery means exchanges and infrastructure providers should prioritize futures market development and support. Increasing liquidity, lowering transaction costs, and enhancing market access improve price discovery.

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