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Information transmission between Bitcoin derivatives and spot markets: High-frequency causality analysis with Fourier approximation

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Abstract

This paper examines the information transmission between Bitcoin derivatives and spot exchanges using 15-minute interval data over May 2016 - September 2020. We employ a novel econometric framework with Fourier approximation, taking structural shifts in causal linkages, on the prices, returns, and volatilities of BitMEX, the derivatives market, and five other major spot exchanges, Coinbase, Bitstamp, Kraken, CEX.io, and Poloniex. Overall, the results provide robust evidence of information flow between the derivatives and spot exchanges, implying the markets react to new information simultaneously. The results are of importance for investors conducting portfolio allocation exercises and risk management strategies.

Keywords: Bitcoin; Price Discovery; High-Frequency Data; Fourier approximation; Structural Shifts
JEL Classification Codes: G12, G15, C13, C32, C58

1. Introduction

As of the end of 2019, the global cryptocurrency market's size has reached $754 million and is projected to reach $1,758 million in 2027 (Fortune Business Insights, 2020); an astounding performance if it is thought the market was created just nine years ago. In addition to spot markets, we observed a remarkable growth in derivative markets of cryptocurrencies; the trading volume of which for the second quarter of 2020 was $2.159 trillion, based on data from 42 exchanges with an increase of 165.56% from the second quarter of 2019 (International Banker, 2020). The Bitcoin perpetual swap contracts (XBT/USD) introduced by BitMEX[1] in May 2016 accelerated this growth more than did the Bitcoin futures trading in the Chicago Board Options Exchange (CBOE) and the Chicago Mercantile Exchange (CME). In their paper, Alexander et al. (2020) discuss the properties of BitMEX, lower margin requirements, lower trading costs, more flexible trading hours, and smaller contract sizes, facilitating investors' easier access to the markets. They also argue that all these features cause a remarkable increase

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in the trading volumes of BitMEX, especially with nose-diving fall from $20,000 levels on December 17, 2017. The daily average volume of swaps traded in BitMEX increased from around 96 to 281 thousand bitcoin from the second half of 2017 through the first half of 2018. Meanwhile, the bitcoin futures traded in CBOE and CME were only around 6 and 14 thousand bitcoin, respectively, for the first half of 2018 (Alexander et al., 2020).

These developments have lured investors, traders, and researchers' attention and driven them to investigate derivatives' role in determining the price in cryptocurrency markets. Theoretically, the relationship between the spot and futures markets depends on the *cost of carry model* and *law of one price*, and empirically, the futures price is often found to lead the price discovery (Baur and Dimpfl, 2019). The main reason behind this might be higher trading volumes in futures than those in spot markets. The higher the trading volume in a market, the more intense information circulation will be along with a more efficient price (Alexander et al., 2020).

There is an established literature on price discovery and efficiency in derivative markets examining different assets, but this subject is recent and still open for further investigation for cryptocurrencies. We can categorize the studies on efficiency and price discovery of cryptocurrency markets into three: The first group consists of papers focusing only on the Bitcoin price in the same market. Several papers find that the market is inefficient but moving toward efficiency over time or showing time-varying efficiency (Urquhart, 2016; Bariviera, 2017; Tiwari et al., 2018; Sensoy, 2019). On the other hand, while Nadarajah and Chu (2017) find that the market is informationally efficient at the weak form, others prove its inefficiency (Jiang et al., 2018; Kristoufek, 2018). In a more comprehensive paper, Brauneis and Mestel (2018) add other cryptocurrencies and find that Bitcoin leads the others, thanks to its highest trading volume. They argue that Bitcoin is the most efficient and hence the least predictable among the others. The second group deals with different spot markets for the same cryptocurrency to determine the contributions of, particularly, Bitcoin exchanges to price discovery. Their analysis includes highly traded spot exchanges with usually high-frequency data (Brandvold et al., 2015; Giudici and Pagnottoni, 2019; Ji et al., 2019; Pagnottoni and Dimpfl, 2019). Among these studies, Brandvold et al. (2015) argue that exchanges with the highest trading volumes are price leaders in terms of information share following by smaller exchanges. Different from these studies, Dimpfl and Petery (2020) consider different levels of noise when evaluating price discovery contributions and argue that traditional measures cannot identify the contributions correctly. Finally, the third group that our paper mostly relates to, considers both the spot and futures market and tries to figure out which plays a leading role in the price discovery process after the introduction of bitcoin futures in CME and CBOE. In comparison, some of them argue that spot leads futures (i.e., Baur and Dimpfl, 2019; Corbet et al., 2018), many prove that the futures dominate the price discovery function (Kapar and Olmo, 2019; Alexander and Heck, 2019; Akyildirim et al., 2019; Alexander et al., 2020; Fassas et al., 2020), consistent with the theory and most of the empirical analysis. Among these papers, Alexander et al. (2020) find that BitMEX perpetual swaps lead prices on major bitcoin spot exchanges indicating its strong price discovery and higher informational efficiency. Unlike existing studies, Lee et al. (2020) examine the markets in terms of arbitrage efficiency and find that futures prices are biased predictors of future spot prices. Entrop et al. (2020) go one step further and investigate the factors that may impact bitcoin price discovery in both spot and futures markets and find a significant time-variation in their contribution to price discovery of both markets. In a more recent paper, Hattori and Ishida (2021) consider Bitcoin futures trading volume to analyze the potential impact of Bitcoin futures on the Bitcoin market crash in December 2017 and find no significant result. Researchers could not reach a single result due to different methods, data sources, settlement prices, frequencies, and timespans. Therefore, following the steps of the last group, this paper reexamines the price discovery function for cryptocurrency markets by considering the perpetual swap contract of BitMEX and the most traded spot exchanges, Coinbase, Bitstamp, Kraken, CEX.io, and Poloniex, using 15-minute data for a more extended period from May 30, 2016, to September 23, 2020.

The paper has four main contributions. First, most papers consider CME and CBOE. However, here we follow Alexander et al. (2020) that consider BitMEX as a proxy for the derivatives market for cryptocurrencies because of its higher trading volume and the reasonable grounds aforementioned in short, albeit in detail in the original work. Different from their study, we consider two more major spot exchanges, CEX.io and Poloniex. Second, our data further extend to that of Alexander et al. (2020) and cover significant events in the cryptocurrency environment and the developments following the emergence of the COVID-19 pandemic. Third, we analyze a high-frequency dataset, 15-minutes interval data, which may be essential for cryptocurrency markets, where the trading continues 24/7, and sudden shifts (i.e., flash crash, spikes) in the prices within a day are usual. Fourth, our study is different from previous studies implementing standard methods ignoring structural breaks in the data. The cryptocurrency markets, as young attractive emerging markets, experience sharp price movements due to several significant developments, such as technical aspects (e.g., halving; security improvements, Taproot, in May 2019; mining difficulty changes in December 2018), centralized exchange hacks (e.g., Bitfinex hack in August 2016), regulatory issues (e.g., the SEC rejecting ETF applications in July 2018, Chinese central bank's statement in November 2019), causing structural breaks in the data. Accordingly, we employ novel unit root and Granger causality tests with Fourier approximations, considering the structural breaks in the data period, which is necessary given the developments in the analyzed data period.

The remainder of the paper is organized as follows. Section 2 documents the methodology; Section 3 presents the data and the empirical results; the last section concludes the paper.

2. Methods

We employ Granger causality tests, following the Toda and Yamamoto (1995) (TY) procedure. The TY procedure does not require pre-checking cointegration and allows using the level form of the series without necessitating stationary ($I(0)$) variables in a vector autoregressive (VAR) model. We estimate the following VAR(p+d) model where d is the maximum degree of integration:

$$y_t = \alpha + \beta_1 y_{t-1} + \ldots + \beta_p y_{t-p} + \ldots + \beta_{p+d} y_{t-(p+d)} + \varepsilon_t \quad (1)$$

where y_t is a vector of k endogenous variables, α is a vector of intercepts, ε_t is a vector of error terms, and β is the matrix of parameters. By imposing zero restriction on the first p parameters in Eq. 1, we obtain *Wald* statistics following χ^2 distribution, with p degrees of freedom, under the null hypothesis of Granger non-causality against the alternative hypothesis of Granger causality.

However, the original TY procedure does not consider structural shifts in the analysis, even though it is robust to unit root. Nazlioglu et al. (2016), Gormus et al. (2018) Nazlioglu et al. (2019) augment the TY procedure with a Fourier approximation, considering structural shifts, relaxing the assumption that the intercepts are constant over time:

$$y_t = \alpha(t) + \beta_1 y_{t-1} + \ldots + \beta_p y_{t-p} + \ldots + \beta_{p+d} y_{t-(p+d)} + \varepsilon_t \quad (2)$$

where $\alpha(t)$ is the Fourier approximation, capturing the structural shifts with an unknown data, number, and form of breaks, as follows:

$$\alpha(t) \cong \alpha_0 + \sum_{k=1}^{n} \alpha_k \sin\left(\frac{2\pi kt}{T}\right) + \sum_{k=1}^{n} \beta_k \cos\left(\frac{2\pi kt}{T}\right) \quad (3)$$

where n is the number of frequencies; k is a particular frequency; α_k and β_k, respectively, measure the amplitude and displacement of the frequency; T is the number of observations (Enders and Lee, 2012; Nazlioglu et al., 2019). Substituting Eq. 3 in Eq. 2, the model is as follows:

$$y_t = \alpha_0 + \sum_{k=1}^{n} \gamma_{1k} \sin\left(\frac{2\pi kt}{T}\right) + \sum_{k=1}^{n} \gamma_{2k} \cos\left(\frac{2\pi kt}{T}\right) + \beta_1 y_{t-1} + \ldots + \beta_p y_{t-p} + \ldots + \beta_{p+d} y_{t-(p+d)} + \varepsilon_t \quad (4)$$

One may estimate the model with a single frequency component, setting n to unity, or estimate the model with cumulative frequencies, setting n greater than unity. For d=0, Eq. 4 simplifies to the VAR model with the Fourier approximation developed by Enders and Jones (2016) to test Granger causality between stationary, $I(0)$, variables.

3. Data and empirical results

We obtain the spot Open, High, Low, and Close (OHLC) prices of Bitcoin from the five major cryptocurrency exchanges, Coinbase (CBS), BitStamp (BTP), Kraken (KRA), CEX.io (CEX), and Poloniex (PLX). The futures OHLC prices of Bitcoin are collected from BitMEX (BMX), which launched perpetual swap contracts quoted in US Dollars. A perpetual swap is similar to conventional futures contracts with several differences. A perpetual swap is a cross-currency between Bitcoin and USD, exchanged between the short- and long-position takers who pay interest on the principal in the currency that they receive. In a perpetual swap contract, different from the currency swaps, there is no settlement date. Given the unique BitMex funding rate calculation and no interest in Bitcoin, unlike traditional currency swaps, perpetual contracts trade close to the underlying reference price, minimizing the basis risk. Different from the CBOE futures of which the contract size is one Bitcoin, BitMex perpetual swaps are traded 24/7 with a contract unit of one USD, providing affordability and liquidity. Following (Alexander, Choi, Park, & Sohn, 2020) and (Alexander & Heck, 2020), we use BitMex perpetual swap contract prices owing to its higher trading volume and accessibility by retail investors. We construct our dataset, exploiting the public application programming interface (API) data repositories of the cryptocurrency exchanges, except Kraken; we get the OHLC data for Kraken from Bitcoincharts.com[1] [2]. The 15-minute interval data cover the period between May 30, 2016, 12:15 AM and September 23, 2020, 12:00 AM.

We analyze natural logarithmic (log) Bitcoin closing prices, returns, and 15-minute variances (volatilities). The log-returns are the first differences of the logarithmic closing prices. Following Diebold and Yilmaz (2012) and Parkinson (1980), the log-volatilities are calculated using the high (P^H) and low (P^L) prices within the 15-minute interval:

$$\tilde{\sigma}_{it}^2 = 0.361\left[\ln\left(P_{it}^H / P_{it}^L\right)\right]^2, \quad (5)$$

Table 1 reports the descriptive statistics of the Bitcoin prices, returns, and annualized volatilities. According to the standard deviation statistics for log-returns, the most volatile exchange is Poloniex, followed by BitMEX; however, the top three volatile exchanges are the spot exchanges, Poloniex, Bitstamp, and CEX.io, in terms of log-volatilities. For all cases, the Jarque-Bera tests suggest rejecting the null hypothesis that a series has a normal distribution.

We check the maximum degree of integration (d) of the series, estimating the ADF unit root tests with Fourier approximation (Enders and Lee, 2012)[3], and report the results in Table 2. The results show that the prices are integrated of order one, $I(1)$, since the returns are stationary, $I(0)$, at the 1% level. Furthermore, the volatility series are also stationary as the Fourier ADF tests suggest rejecting the null hypothesis of unit root at the 1% level. Overall, the unit root test results suggest setting d to unity and testing the Granger causality following the TY procedure, specified in Eq. 4. We estimate the model developed by Enders and Jones (2016) for the *stationary* returns and volatilities, where d is set to zero.

[1] The *Python* codes to obtain the high-frequency data are available upon request from the corresponding author.
[2] https://bitcoincharts.com/
[3] We do not provide the details for the unit root test to conserve space; the reader is referred to the cited paper for the details.

Table 1. Descriptive Statistics.

	Mean	Std. Dev.	Skewness	Kurtosis	J-B
Log-Price					
BMX	8.352	0.982	-0.893	2.401	22365 [a]
CBS	8.351	0.982	-0.894	2.399	22423 [a]
BTP	8.369	0.980	-0.896	2.431	22294 [a]
KRA	8.353	0.981	-0.892	2.402	22338 [a]
CEX	8.352	0.981	-0.892	2.397	22382 [a]
PLX	8.353	0.980	-0.896	2.402	22489 [a]
Log-Return (%)					
BMX	0.002	0.383	-0.682	104.225	64645859 [a]
CBS	0.002	0.373	-0.493	107.833	69330565 [a]
BTP	0.002	0.353	0.184	96.112	54689936 [a]
KRA	0.002	0.378	-0.167	172.061	180000000 [a]
CEX	0.002	0.376	-0.466	101.214	60851892 [a]
PLX	0.002	0.403	-0.292	81.361	38735576 [a]
Log-Volatility (%)					
BMX	2.139	1.460	-1.092	5.541	70810 [a]
CBS	2.740	1.210	-1.711	8.606	272110 [a]
BTP	2.131	1.670	-2.082	10.397	454510 [a]
KRA	2.221	1.253	-1.123	6.347	102516 [a]
CEX	2.170	1.633	-1.519	6.840	151234 [a]
PLX	3.507	2.001	-6.564	61.220	22468675 [a]

Notes: [a] denotes statistical significance at the 1% level. J-B is the (Jarque and Bera, 1980) normality test with the null hypothesis that a series has a normal distribution.

Table 2. Fourier ADF Unit Root Test (Enders and Lee, 2012).

	Log-Prices			Log-Returns			Log-Volatility		
	ADF	**Freq**	**Lag**	**ADF**	**Freq**	**Lag**	**ADF**	**Freq**	**Lag**
BMX	-2.197	2	10	-124.473 [a]	2	9	-26.721 [a]	1	24
CBS	-2.184	2	9	-134.650 [a]	2	8	-31.135 [a]	2	24
BTP	-2.205	2	9	-134.033 [a]	2	8	-32.454 [a]	2	24
KRA	-2.237	2	5	-175.983 [a]	2	4	-35.566 [a]	2	24
CEX	-2.112	2	9	-133.907 [a]	2	8	-35.795 [a]	1	24
PLX	-2.196	2	14	-107.227 [a]	2	13	-41.559 [a]	2	24

Notes: [a] denotes statistical significance at the 1% level. The maximum number of Fourier frequencies (k_{max}) and lag lengths (p_{max}) are, respectively, three and 24.

Table 3 presents the TY Granger causality testing results for the prices. We estimate bi-variate VAR models with two price series – BitMEX futures prices and spot prices from one of the spot exchanges, Coinbase, Bitstamp, Kraken, CEX.io, and Poloniex. Both the conventional TY and Fourier TY causality tests suggest rejecting the null hypothesis that BitMEX futures prices do not Granger cause the spot prices at the 1% level.

We can reject the null hypothesis of no Granger causality from the spot prices to BitMEX futures prices, at the 1% level, for all spot exchanges, except CEX.io, where the causality evidence is significant at the 5% level. The results imply robust evidence of bi-directional information transmission between the prices of futures and spot exchanges.

Table 4 shows the results of the Granger causality tests on the *stationary* returns. Based on both the standard and Fourier Granger causality tests, we reject the null hypothesis of no causality between the returns of futures and spot markets at the 1% level, implying a significant bi-directional information transmission. The results are consistent with those on the prices, implying robust evidence of mean transmission between the derivatives and spot exchanges.

Table 3. Toda & Yamamoto Granger Causality Test, Log-Prices.

	Standard Toda & Yamamoto		**Single Fourier-frequency Toda & Yamamoto**			**Cumulative Fourier-frequency Toda & Yamamoto**		
	Wald	**Lag**	**Wald**	**Lag**	**Freq.**	**Wald**	**Lag**	**Freq.**
BMX≠>CBS	365.632 (0.000)	14	366.349 (0.000)	14	1	366.414 (0.000)	14	3
CBS≠>BMX	3176.553 (0.000)	14	3176.499 (0.000)	14	1	3175.887 (0.000)	14	3
BMX≠>BTP	1695371.649 (0.000)	23	1695802.138 (0.000)	23	1	1695782.039 (0.000)	23	3
BTP≠>BMX	75.385 (0.000)	23	76.446 (0.000)	23	1	79.033 (0.001)	23	3
BMX≠>KRA	2397.248 (0.000)	15	2396.761 (0.000)	15	3	2394.400 (0.000)	15	3
KRA≠>BMX	1032.196 (0.000)	15	1032.886 (0.000)	15	3	1034.523 (0.000)	15	3
BMX≠>CEX	27.061 (0.000)	6	26.969 (0.001)	6	1	26.643 (0.000)	6	3
CEX≠>BMX	17.461 (0.008)	6	17.591 (0.012)	6	1	17.974 (0.012)	6	3
BMX≠>PLX	2002.915 (0.000)	17	2002.912 (0.000)	17	2	2002.856 (0.000)	17	3
PLX≠>BMX	82025.223 (0.000)	17	82034.474 (0.000)	17	2	82036.025 (0.000)	17	3

Notes: The numbers in parentheses are bootstrapped p-values obtained from 1,000 repetitions. The maximum number of Fourier frequencies (k_{max}) and lag lengths (p_{max}) are, respectively, three and 24. The Fourier frequencies (k) and lag lengths (p) are determined by the Schwarz Information Criteria.

Table 4. Granger Causality, Log-Returns.

	Standard Granger Causality		**Single Fourier-frequency Granger Causality**			**Cumulative Fourier-frequency Granger Causality**		
	Wald	**Lag**	**Wald**	**Lag**	**Freq.**	**Wald**	**Lag**	**Freq.**
BMX≠>CBS	382.232 (0.000)	18	382.232 (0.000)	18	2	382.362 (0.000)	18	3
CBS≠>BMX	3117.944 (0.000)	18	3117.537 (0.000)	18	2	3116.781 (0.000)	18	3
BMX≠>BTP	1683037.118 (0.000)	22	1682954.976 (0.000)	22	2	1682835.194 (0.000)	22	3
BTP≠>BMX	75.781 (0.002)	22	75.892 (0.000)	22	2	76.030 (0.000)	22	3
BMX≠>KRA	2424.747 (0.000)	23	2424.539 (0.000)	23	2	2424.560 (0.000)	23	3
KRA≠>BMX	1055.888 (0.000)	23	1055.677 (0.000)	23	2	1055.232 (0.000)	23	3
BMX≠>CEX	25.792 (0.000)	5	25.968 (0.000)	5	2	26.216 (0.000)	5	3
CEX≠>BMX	17.977 (0.002)	5	17.772 (0.007)	5	2	17.489 (0.007)	5	3
BMX≠>PLX	2002.997 (0.000)	16	2002.977 (0.000)	16	2	2002.890 (0.000)	16	3
PLX≠>BMX	81894.767 (0.000)	16	81891.082 (0.000)	16	2	81884.569 (0.000)	16	3

Notes: See the notes for Table 3.

Table 5. Granger Causality, Log-Volatilities.

	Standard Granger Causality		Single Fourier-frequency Granger Causality			Cumulative Fourier-frequency Granger Causality		
	Wald	**Lag**	**Wald**	**Lag**	**Freq.**	**Wald**	**Lag**	**Freq.**
BMX=>CBS	1162.672 (0.000)	24	1517.544 (0.000)	24	1	1418.763 (0.000)	24	3
CBS=>BMX	515.958 (0.000)	24	571.150 (0.000)	24	1	736.064 (0.000)	24	3
BMX=>BTP	18387.583 (0.000)	24	18350.513 (0.000)	24	2	18252.321 (0.000)	24	3
BTP=>BMX	354.322 (0.000)	24	250.131 (0.000)	24	2	245.334 (0.000)	24	3
BMX=>KRA	1998.554 (0.000)	24	2255.319 (0.000)	24	1	1901.932 (0.000)	24	3
KRA=>BMX	621.141 (0.000)	24	670.037 (0.000)	24	1	675.230 (0.000)	24	3
BMX=>CEX	217.183 (0.000)	24	229.470 (0.000)	24	2	123.111 (0.000)	24	3
CEX=>BMX	182.554 (0.000)	24	237.219 (0.000)	24	2	167.073 (0.000)	24	3
BMX=>PLX	1245.822 (0.000)	24	1826.597 (0.000)	24	1	1615.405 (0.000)	24	3
PLX=>BMX	762.595 (0.000)	24	824.691 (0.000)	24	1	857.706 (0.000)	24	3

Notes: See the notes for Table 3.

In addition to the causality in prices and returns, we check the causal relationship between the volatilities of the exchanges. Table 5 reports the results on the stationary volatilities, 15-minute variances. Consistent with the previous results, both the standard and Fourier causality tests provide strong evidence of bi-directional Granger causality between the volatilities of the spot and futures exchanges at the 1% level.

Overall, the magnitudes of the Wald statistics are large, pointing out strong evidence of information transmission between prices, returns, and volatilities of futures and spot markets. The Wald statistics are larger for the causality running from the prices and returns of BitMEX to those of Bitstamp, Kraken, and CEX.io, and vice versa for the remaining spot exchanges, Coinbase and Poloniex. The differences in Wald statistics magnitudes are more evident for Coinbase, Bitstamp, and Poloniex than for the other spot exchanges. Furthermore, for the causality analysis on the volatilities, the Wald statistics are larger for the volatility transmissions from BitMEX to all spot exchanges. Both the standard and Fourier models suggest rejecting the non-transmission at the 5% level or better, implying a robust conclusion of mean and volatility transmissions between futures and spot exchanges, even after controlling for structural shifts.

4. Concluding remarks

The paper examines the information transmission between Bitcoin derivatives and spot markets, considering the structural shifts in the data. The above methodology with Fourier approximation is used for the first time to examine the causal linkages between the prices, returns, and volatilities of BitMEX, the derivatives exchange, and those of the selected spot exchanges, Coinbase, Bitstamp, Kraken, CEX.io, and Poloniex. The results obtained from both the standard and Fourier Granger causality tests lead to a robust conclusion of bi-directional information (i.e., prices, returns, and volatilities) transmission between the Bitcoin futures and spot markets, even in the presence of structural breaks. Particularly, Coinbase, the largest spot exchange in terms of trading volume, and Poloniex, the most volatile spot exchange, lead the price discovery process. Specifically, the BitMEX futures market's price discovery role is comparably dominant on the Bitstamp spot exchange. Our results are of importance for investors conducting asset allocation and risk management strategies and taking positions in the derivatives and different spot exchanges of Bitcoin. Academics may exploit the results for developing asset pricing models considering structural shifts in the parameters via Fourier approximation. Future work may analyze the dynamic connectedness of the derivatives and spot exchanges and assess the hedging effectiveness of taking long and short positions in the exchanges.

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