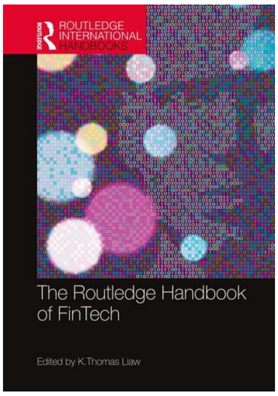

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PRICE DISCOVERY IN THE BITCOIN FUTURES AND CASH MARKETS

Tatja Karkkainen[1]

1 Introduction

This study investigates whether the Bitcoin market price discovery is led by the futures market, and its traditionally higher concentration of informed traders, over the Bitcoin exchanges. Building on the preceding literature on price discovery in futures and spot markets, around 75% of the new information was first impounded in the futures markets, as was already suggested in the early 1980s by Garbade and Silber (1983).

Bitcoin futures contracts were introduced to the marketplace in December 2017 as the first institutional standard cryptocurrency derivative. The contracts were launched to the market by the two globally largest futures and options exchanges, namely Chicago Mercantile Exchange (CME) and Chicago Board Options Exchange (CBOE). After half a year, the engagement in these contracts by informed or uninformed traders has been limited and volumes have remained comparatively low to date.

The Bitcoin was originally designed as a decentralised and private money payment system with founding motivations to facilitate irreversible online transactions (Nakamoto, 2008). Since then, this cryptocurrency has found popularity as a store of value. Bitcoin is claimed to be lacking the characteristics of behaving like a currency, in terms of functioning efficiently and reliably as a means of exchange, store of value or unit of account (Baur and Dimpfl, 2017). Whilst the Bitcoin can be thought to have the potential of those functions that are thought to describe a currency, it does not currently consistently act in this role due its high price volatility. Moreover, its increase in popularity has increased the payment transaction costs. An overview of economic and technical aspects of Bitcoin and its blockchain can be viewed in studies, e.g. Böhme et al. (2015), Dwyer (2015), Yermack (2013).

The analysis on Google trends and Bitcoin price research by Kristoufek (2013) suggest that whilst cryptocurrencies can be recognised as new financial instruments, they do not have underlying assets, or such related fundamentals, and subsequently will be traded on sentiment. The same paper also found evidence on prevalent momentum trading on Bitcoin. Momentum trading strategies may be connected with noise trading. For example, McMillan and Speigh's (2006) study of FTSE-100 Index and futures intra-day prices suggests that noise driven momentum trading is prevalent in rising markets, but such activity has a weaker relationship during falling markets when fundamental based trading is more pronounced.

Due to the lack of tangible fundamental valuation and the ensuing downside volatility, such a trading pattern may not be suitable to describe Bitcoin trading.

Using data between 2009 and mid-2017, Baur and Dimpfl (2017) found that Bitcoin behaves neither like a traditional fiat currency nor like gold. Unlike fiat currencies, the supply of Bitcoin is exogenous (Ciaian et al. 2015). As early as the 1970s, Friedrich Hayek[2] voiced his views on libertarian private money and de-nationalisation of currencies that stand independent from central banks and monetary policies. In the same vein, in 1999, Milton Friedman[3] suggested that currencies – such as today's Bitcoin – could be facilitated by the Internet. The cryptocurrencies only properly took off after the 2007–2008 global financial crisis and the aftermath that included quantitative easing by central banks.

The Bitcoin was designed to follow the economics of gold mining (Nakamoto, 2008). Like gold, Bitcoin has an element of scarcity via its finite stock (Böhme et al., 2015) Moreover, procedurally, Bitcoin mining requires computing and electricity resources (Garcia et al., 2014). The cost of mining new Bitcoins and transaction confirmation might be the only traditional fundamental value constituents for the Bitcoin pricing. By 2020, around 1,800 new Bitcoins are expected to be created each day, whose value will fluctuate with the popularity of the coin. The supply of the planned final Bitcoin amount is fixed at 21 million, after which the miners are only remunerated by transaction confirmation fees denominated in Bitcoins. Currently, the price of the mining can fluctuate as the Bitcoin block chain verification related mathematical problem increases or decreases in difficulty depending on the computing power available in the mining network. Since 2017, this difficulty has been increasing exponentially[4] and this impacts the economic pay-off for the miners.

Price discovery is the process in which new trading information incorporates into the efficient market price of an underlying asset (Hasbrouck, 1995; Lehmann, 2002). It can take place across various marketplaces and instruments. However, the efficient price should not be identified as the asset's fundamental value, which is based on, for example, estimating the present value of future cash flows. Price discovery is an important attribute of the markets which are deemed fragmented, as are those for Bitcoins (Hasbrouck, 1995).

Bitcoin is a payment system whose aim was to have no centralisation of influence. However, there is evidence that individually Bitcoin exchanges can be perceived to have a significant influence on the cryptocurrency prices (Gandal et al., 2017; Brandvold et al., 2015; Moore and Christin, 2013). This would have a significant impact on the asset's long-term price and price discovery.

In parallel studies of Bitcoin cash market and futures market price discovery, Kapar and Olmo (2019) analyse the daily prices and similarly find that futures are leading the spot market. In contrast, however, Baur and Dimpfl (2019) find evidence of spot leading the futures through their treatment of futures prices using three-month to expiry rather than the nearest month-end expiry. This has its challenges as the longer futures contracts have very low volumes and there is also an issue with the reliability of the spot price information from the cryptocurrency exchanges. Their study does not offer a separate impact analysis of the nearer expiry futures contracts on the longer-term futures contracts or the spot prices.

Alexander and Heck (2019) also find evidence of futures leading the spot market. Their study uses traded futures contracts price information instead of quoted mid-prices. The mid-prices encapsulate the price discovery that is communication of the asset price among buyers and sellers in the marketplace. This specification is used in this chapter.

There are previous studies conducted on Bitcoin price determining factor analysis (e.g. Zhu et al. 2017; Ciaian et al., 2015) and specifically on Bitcoin exchanges price discovery (Brandvold et al., 2015; Pieters and Vivanco, 2017), before the introduction of the futures.

This study contributes to the existing price discovery literature of Bitcoin by providing empirical investigation on comparing the spot market and futures market with novel data. The sample is analysed at different frequencies for robustness purposes.

The rest of this study is organised as follows: Section 2 introduces the Bitcoin future contracts and the Bitcoin exchanges. Moreover, it situates this investigation in the existing price discovery literature. Section 3 describes the data and the empirical strategy methodologies for examining Bitcoin futures and the cash market interaction. Section 4 presents and discusses the results. Finally, section 5 concludes.

2 Background: Bitcoin exchanges, futures and price discovery

Futures were introduced into a global Bitcoin market that trades across many exchanges 24 hours and 7 days a week. The Bitcoin market is known for its volatility and its frictions. Price discovery methodologies provide an opportunity to compare this new financial instrument with the older innovation. The futures introduction and trading is a well-researched area in market microstructures. This may enable making predictions of the change in the marketplace. For example, the introduction of financial futures can improve the liquidity of the underlying market (Garbade and Silber, 1983) as well as facilitate risk transfer from hedgers to speculators (Working, 1962; Silber, 1985). Further, the introduction of futures may also contribute to an immediate reduction in spot market volatility (Bologna and Cavallo, 2012).

Introduction of the futures may also have alternative influences to the spot market. Witherspoon (1993) proposed that whilst futures can dominate price discovery in the marketplace, if the initial and maintenance margins are set too high either by regulatory policy or by market practise, these can effectively contribute to the spot market bubble or crash. The introduction of futures may offer the investors, especially the smart money investors, an efficient tool for potentially shorting the overpriced market (Shiller, 2003). After the introduction of the Bitcoin futures, the market saw a large price correction.

Lyons (1995) and Rosenberg and Traube (2006) compared the price determination and the trading volume sizes of the currency spot market with the futures market and noted that the futures market can exhibit a significant price discovery with a much lower volume. Similar to the currency market structure characteristics, Bitcoin futures trading volume is minuscule compared to the spot market. This trading volume is around 1,000 times lower.[5] This is opposite to the gold investment market, where the futures exhibit much higher volume compared to the spot market. A potential explanation for the relatively low Bitcoin futures trading may be the higher barrier to entry for retail traders compared to the Bitcoin exchange trading and relative absence of institutions in the entire Bitcoin marketplace to contribute to the market size.

Rosenberg and Traube (2006) have suggested that the derivatives market, in this case the futures market, can attract more informed traders. This is due to lower fees, access to leverage, anonymity of trading or higher speed of trade execution. Hence, they can exhibit a disproportionately much higher price determination effect relative to their lower trading volume. In addition, futures can also enable a short exposure to the market. Nonetheless, some of these features, such as leverage and asset shorting, are already available for traders at some of the Bitcoin exchanges. Generally, the undiscounted Bitcoin investment transaction fees, charged by cryptocurrency exchanges, are lower compared to the Bitcoin futures bought through brokers.

Böhl et al. (2011) suggested that futures and spot markets' price discovery can relate to the investor composition and to the differences between institutional and retail investor trading.[6] If the futures market trading is dominated by uninformed retail investors, it would not contribute to the price discovery of the assigned market. Whereas there is evidence on the prevalence of sophisticated traders in the Bitcoin markets, for example those using algorithmic trading, the evidence on the wider take-up by institutional investors is not as clear. Traditionally institutions are recognised for their larger transaction volumes as well as their preference for 'buy-and-hold' strategies, as well as fundamental value investing. Institutional investors may also face further restrictions in trading Bitcoin. For instance, it remains unclear how cryptocurrencies should be treated by the banks in Basel II/III regimes (Peters et al., 2016).

The Bitcoin futures are priced and settled in US dollars, while the Bitcoin exchanges facilitate trading Bitcoin in other foreign currencies and cryptocurrencies such as Ethereum, Ripple and Litecoin. At launch, the CBOE Bitcoin futures had initial margins at 44% with similar maintenance margins. These are much higher margins when compared to, for example, gold or FX futures.[7] Subsequently, these margin levels result in lower leverage than usual for futures contracts. The underlying historic market volatility contributes to the level of the margin requirement and Bitcoin has been extraordinarily volatile compared to other assets or currencies (Kasper, 2017). This volatility may have been further fuelled by leveraged purchases with credit cards[8] and by up to 15-time leverage[9] on exchanges. There are also exchanges that offer derivatives on Bitcoin, but there have been difficulties with clearing these trades.

A CBOE Futures contract unit equals one Bitcoin. The CBOE exchange's typical trading hours apply with only a partial weekend trading and 15 minutes closing period for settlements during the weekdays. The contract is priced off on an auction at 3pm Central Time on a Gemini cryptocurrency exchange. There is a discretionary 20% daily price fluctuation trading cap. On the whole, the CBOE futures are quite similar to the CME futures. However, they have differentiated contract sizes and strike price calculation mechanisms. Namely, CME's minimum contracts size is 5 Bitcoins and their contract is priced by a CME Bitcoin Reference Rate constructed with a few Bitcoin exchanges; namely GDAX, Kraken, itBIT, Bitstamp and Lakebit exchanges during 3–4pm trading (Painem and Knottenbelt, 2016; Crypto Facilities. 2017). It appears that CBOE is seeking to offer higher technologically advanced trading and appealing to both retail and institutional traders, while CME continues to appeal to institutional clientele. The CME Bitcoin futures trade at higher volumes.

The Bitcoin futures market has natural hedgers, who are the Bitcoin miners. Currently, a single Bitcoin block mining compensates a miner with 12.5 Bitcoins as well as with the aforementioned transaction fees, which are also denominated in Bitcoins. A new block with thousands of transactions is mined every 10 minutes. In total, up to 1800 new Bitcoins are produced each day until the estimated 2020. After this, the number of Bitcoin compensation to miners will halve further and represent 6.25 Bitcoins per a block. Only 21m Bitcoin tokens can be mined, after which the miners will be compensated only with transaction fees.

As the current Bitcoin futures are cash settled, miners who might seek to participate in hedging their long-term mining activities, and their Bitcoin price exposure, would be required to exchange the mined Bitcoins or transactions fees to cash at the Bitcoin exchanges before settling the futures trades or margins with the broker. This process further makes the miners reliant on the Bitcoin exchanges, and the process is cumbersome even without considering the futures' high margin premiums.

Considering that CME and CBOE had their own base initial and maintenance margins, the brokers, through which the hedgers act, can demand even higher requirements. These high margins could be possibly avoided if the futures contracts were also directly settled by

Bitcoin. This would additionally provide a direct portfolio diversification benefit for speculators who are the counterparties for these trades.

In addition to selecting the preferred trading instruments, access to the price information can also influence traders' trading decisions. While the bid-and-ask order book information is readily available to traders at the Bitcoin exchanges, there are higher barriers when accessing live information on Bitcoin futures bid–ask quotes. This information can be accessed through a broker or the futures exchange at an additional fee. Subsequently, this distinct access to data could create an informational advantage (Ito et al., 1998). Nevertheless, algorithmic trading in the Bitcoin markets and the opportunity to arbitrage, as well as enhanced monitoring and trading technologies, can reduce the price differences between the marketplaces (Hendershott and Riordan, 2013). To make for an efficient marketplace, the arbitrage enabling conditions need to be present so that the prices of different instruments for the same underlying would not diverge (Hasbrouck, 1995). The price quotes of the same underlying in the various market place are assumed to converge in the long run (de Jong et al., 2001).

The significance of trading information sourcing is also supported by price discovery studies by Tse et al. (2006) and Hasbrouck (2003). Tse et al. (2006) compared Euro and Yen FX traded on the futures electronic markets, futures trading floor and electronic retail spot market. They found that the traders favoured electronic marketplaces for their immediate, anonymous trading capacity and transparent pricing. Therefore, the futures and retail spot markets led price discovery over the futures physically traded in the pits. As with the trading pit and with the bank interdealer FX platforms, where most trading took place, these marketplaces offered simultaneously different exchange prices. This would suggest a frictional marketplace where the best pricing information leads.

Hasbrouck's (2003) price discovery study on US Equity Market Indices focused on the relationship between the E-mini futures that are traded electronically, traditional pit traded futures and exchange traded funds (EFTs). The study discovered that E-mini futures, which were available for S&P 500, dominated with over 90% of the price discovery. This is with making an allowance for pit traded futures' lower fees, higher cash nominated volumes and open interest. The E-minis trading was shown to have an informational advantage and enhanced price transparency by means of disclosing the real time bids, asks and market depths.

While the contemporaneous differences in the exchanges' Bitcoin returns can indicate arbitrage opportunities,[10] there are considerations over the fees, liquidity and exchange access (Kroeger and Sarkar, 2016). Previous studies have carried out a case for arbitrage trading opportunities across various Bitcoin exchanges due to continuing market frictions (e.g Kristoufek, 2015; Pieters and Vivanco, 2017; Halaburda and Gandal, 2014). This is also backed by the existence of traders employing arbitrage strategies in Bitcoin markets. Understanding of the major and satellite markets can be important for fully grasping the market dynamics (Garbade and Silber, 1983). Furthermore, the Bitcoin prices can vary between the larger and smaller regional markets due to volume differences and market access which contribute to a frictional marketplace.

Considering that Bitcoin exchanges were only recently established, this can coincide with higher predisposal to operational difficulties such as downtimes due to high volume of users,[11] denial of service attacks, or hacking. An additional benefit for trading futures has been demonstrated to be that Bitcoin exchanges have also been subject to suspicious trading activity or theft on certain occasions (Gandal et al., 2017; Moore and Christin, 2013). There have also been instances of exchanges founded on a purely fraudulent intent (Vasek and Moore, 2015). In addition to the exchanges, there are claims that other cryptocurrencies facilitated by lax regulation have had a large influence on the Bitcoin price (Griffin and Shams, 2020).

Brandvold et al. (2015) found that larger exchanges by trading volume led price discovery and smaller exchanges followed with a lag with especially Mt. Gox demonstrating a dominating information share. Before Mt. Gox exchange was forced to shut down, the traders customarily paid premium on their Bitcoins due to a fraudulent trading activity, and this had a significant impact on the Bitcoin price rise across the whole market (Gandal et al., 2017). Noting this, large price deviations between a single and groups of exchanges could help to identify enhanced risk (Brandvold et al. 2015). These price distortions can be substantial in size or duration, as was evidenced in the example of the Mt. Gox collapse.

At the outset, Bitcoin market enjoyed a low supervisory regime which may have encouraged exchanges in engaging activities that contributed to the further volatility, instead of only contributing to the price discovery through their microstructure specifications in a frictional marketplace. The presumption is that the Bitcoin futures marketplace is not only more informative, but also the futures are more efficient financial instruments compared to the cash market that is largely unregulated, having varied quality exchanges and driven by retail investors.

3 Data and methodology

Figure 9.1 depicts volatile but also cointegrated 1-minute time series of spot-futures markets. To measure this relationship, Johansen co-integration, Granger Causality and VECM methodologies with also Information Share (IS) and Component Share (CS) tests are applied.

Following Tse et al. (2006) specified *relativeness* of price discovery acknowledging that the causes of the price changes may not be initiated in these marketplaces. Therefore, the study will not endeavour to research areas of macro factor analysis and cross-asset valuation.

This study examines the price discovery relationship between spot and futures markets during the first 5 months of trading between 13 December 2017 and 16 May 2018. Spot market is represented by the US$ denominated Bitcoin Coindesk simple unweighted average of minute-level frequency index. This is generated via four main Bitcoin exchanges'

Figure 9.1 Bitcoin spot and futures market 1-minute frequency

Notes: Red: Represents the CBOE Bitcoin Futures Prices. Blue: Represents the Spot Market Index Bitcoin Prices. 1-minute level data from Coindesk. Translated from the US$.

Source: Sample data captured between 2017.12.13 to 2018.05.16 (UCT) mid-price.[12] Then, the futures mid-price order book data of the CBOE Bitcoin futures is sampled.[13] The preference on the bid-and-ask data, or mid-price, draws on the possibility of being able to trade at those prices on that captioned time.

When constructing the CBOE Bitcoin futures' continuing time series with mid-book prices and noting the various contract expiry dates, only the 1-month duration contracts to their nearest settlement were selected for the time series. At the settlement, the prices were rolled over on to the next month contracts. These 1-month contracts significantly dominate the open interest volume over other contracts. The CBOE Bitcoin futures data were selected for this analysis over the CME Bitcoin trading data, even considering the CME Bitcoin contracts' higher trading volume, due to CBOE Bitcoin futures' earlier launch by a week. When there are no available trades and simultaneously reported bid–ask quotes, these observations are omitted, as are the periods when the futures markets are closed for trading.[14] Altogether 575,615 (long) CBOE Bitcoin Futures contracts were traded on 403,907 separate occasions during the sample period. The sample data order book shows maximum spread of US$350 with minimum of US$0 with an average spread of US$22 with US$18 of standard deviation. In the CBOE Bitcoin futures sample data, the average contract order size is 1.4 with 1.1 standard deviation.

Irregular quoting can be an effect of absence of volume and liquidity, as implied by Andersen (2000) in an examination of high frequency time series data.[15] With electronic trading, this requirement is even more pronounced. At the time of the study, the Bitcoin futures remain a relatively thinly traded instrument, compared to the higher volume Bitcoin exchange trading. To overcome this limitation, the intra-day data will be tested on a variety of frequencies. The price discovery is tested at 1-minute, 5-minute, 15-minute, 30-minute, 1-hour and 1-day frequencies. This also offers benefits with treating the random walk components at different frequencies as well as the white noise. Whilst there is 1-second level data available for the Bitcoin spot market index, the zero median result at the highest frequencies in Table 9.1 points out the infrequency of change in the futures pricing quote in the median return row. Further descriptive statistics are provided before the methodology overview.

The average prices for the spot and futures are roughly similar in the comparable samples. For instance, at 1-minute data frequency level that has 78,720 observations, the spot market's mean price is 10,453 US$ with 2,775 US$ of standard deviation compared to the futures market equivalents at 10,479 US$ and 2,833 US$. For the daily data sample, the spot market's mean price is 10,432 US$ with 2,910 US$ standard deviation and similarly 10,458 US$ with 2,959 US$ for the futures.

Table 9.1 describes the Bitcoin spot and futures series' return statistics. The average return is negative for the spots and futures in all of the frequency samples. The spot market's daily mean return is equal to -0.6% with a standard deviation of 6.3%. The results are similar to the futures market with daily average of -0.7% and 6% of standard deviation. The spot and futures returns are positively skewed for the intra-day data. The excess kurtosis for spot and futures intra-day samples and for the daily spot market sample, suggests leptokurtic distribution with higher amount of return observations in the tails. The range of daily returns for spot market is from -24.4% to 13.1%, while the range for futures returns is lower at -17.7% to 13.7%.

Table 9.2 describes the increasing spot-futures return correlation at lower frequencies. Namely, the minute level 0.67 correlation increases to 0.86 for 1-hour and finally to 0.90 daily correlation. Noteworthy is the standard deviation of the 1-minute level return sample is higher by 0.05% and that the spot market has a remarkably higher excess kurtosis at 1-minute level implying for more outliers.

Table 9.1 Summary statistics. Coindesk Bitcoin Index (Spot) and CBOE Futures (Futures) Returns

	Spot	*Futures*	*Spot*	*Futures*	*Spot*	*Futures*	*Spot*	*Futures*	*Spot*	*Futures*	*Spot*	*Futures*
Returns	*1 minute*		*5 minutes*		*15 minutes*		*30 minutes*		*1 hour*		*1 day*	
Min (%)	−9.2%	−9.1%	−8.9%	−9.4%	−8.9%	−9.3%	−8.7%	−9.3%	−11.7%	−10.2%	−24.4%	−17.7%
1% (returns %)	−0.6%	−0.8%	−1.3%	−1.4%	−2.3%	−2.3%	−3.4%	−3.5%	−4.4%	−4.5%	−19.5%	−13.4%
5% (returns %)	−0.3%	−0.4%	−0.7%	−0.7%	−1.2%	−1.2%	−1.6%	−1.7%	−2.4%	−2.4%	−11.4%	−11.1%
10% (returns %)	−0.2%	−0.3%	−0.4%	−0.5%	−0.8%	−0.8%	−1.1%	−1.1%	−1.7%	−1.7%	−8.8%	−8.6%
Median (returns %)	8.5e−06%	0%	1.8e−06%	0%	1.6e−05%	0%	−3.9e−05%	0%	6.8e−05%	0%	0.1%	−0.2%
90% (returns %)	0.2%	0.3%	0.4%	0.4%	0.7%	0.7%	1.0%	1.0%	1.4%	1.5%	6.1%	6.3%
95% (returns %)	0.3%	0.4%	0.6%	0.6%	1.1%	1.1%	1.6%	1.6%	2.3%	2.2%	9.7%	10.2%
99% (returns %)	0.6%	0.8%	1.3%	1.4%	2.2%	2.3%	3.1%	3.1%	4.4%	4.2%	12.7%	13.4%
Max (returns %)	13.0%	13.0%	12.8%	13.3%	12.9%	13.7%	12.5%	13.7%	12.7%	13.7%	13.1%	13.7%
Mean (returns %)	−8.9e−06%	−9.6e−06%	−2.9e−05%	−3.1e−05%	−8.2e−05%	−8.5e−05%	−0.016%	−0.017%	−0.03%	−0.03%	−0.6%	−0.7%
SD (returns %)	0.23%	0.27%	0.5%	0.5%	0.8%	0.8%	1.1%	1.1%	1.6%	1.6%	6.3%	6.0%
Skewness	2.2	1.5	1.0	1.0	0.8	0.6	0.5	0.4	0.3	0.3	−0.7	−0.1
Excess Kurtosis	219	108	49	45	19.3	20.1	13.1	13.1	8.6	8.7	1.4	0.1
No. of Observations	*78,720*	*78,720*	*24,928*	*24,928*	*8,963*	*8,963*	*4,567*	*4,567*	*2,293*	*2,293*	*103*	*103*

Notes: Returns were transformed from prices in the sample data during the time period from 2017.12.13 to 2018.05.16 (UCT)

Table 9.2 Correlations of CBOE Futures and Coindesk Index Returns

	1 min	*5 min*	*15 min*	*30 min*	*1 hour*	*1 day*
Correlation	0.67	0.71	0.80	0.83	0.86	0.90
No. of Observations	*78,720*	*24,928*	*8,963*	*4,567*	*2,293*	*103*

Notes: Time period 2017.12.13 to 2018.05.16 (UCT)

3.1 Cointegration of the price series

Prior to identifying a significant lead–lag relationship between the futures and spot markets, first cointegration must be determined. Cointegration measurement involves identification of the time series' long run relationship and the series' sensitivity to the estimated efficient price. The Johansen's cointegration test procedure is applied to the spot and futures prices at the various frequencies. In preparation, each of the series' logarithmic prices' non-stationarity are examined with augmented Dickey–Fuller unit root (ADF) test. ADF test can be described as follows:

$$\Delta Y_t = \alpha + \beta Y_{t-1} + \delta \Delta Y_{t-1} + \delta_2 \Delta Y_{t-2} + + \delta_n \Delta Y_{t-N\varepsilon t} \quad (1)$$

where: ΔY is the change at the Bitcoin index and Bitcoin futures log prices, α is a constant and β the coefficient of the long-term trend. If β = 0, the sample can be identified as non-stationary. When determining the lags for all the tests in this study, the most parsimonious model specification used will be that identified by either Akaike (AIC), Hannan–Quinn (HQ) or Bayesian (BIC) information criteria. The ADF test identifies the examined series log prices non-stationary at all frequencies at 1% critical value level.

The Johansen test utilises a maximum likelihood estimator for a cointegrated system with Gaussian errors. According to Johansen (1991), the starting point is the transformation of the Vector Autoregression model (VAR) of two non-stationary time series into a Vector Error Correction Model (VECM).[16] This can be written as:

$$\Delta Y_t = \mu + \sum_{i=1}^{k-1} \Gamma_j \Delta Y_{tk} + \Pi Y_{t-1} + \varepsilon \quad (2)$$

where: ΔYt is the first difference of the assessed two non-stationary variables. Γ is the n × r matrix of coefficients and Π represents the coefficient matrix; k denotes the lag length and μ is a constant term which will be ignored in this model. This study uses the trace model specification of the Johansen test owning to its more powerful estimation capability in smaller data samples, compared to the maximum eigenvalue test. The daily data has only 104 full day observations. For the intra-day data, and their higher observation number, using either Johansen test specification would not induce much concern (Lütkepohl et al., 2001). Formulating the trace test's null hypothesis of no co-integrating vectors (H_0: r = 0) against the alternative hypothesis of one co-integrating vector (H_1: r > 0), the test can be expressed as:

$$\lambda_{trace}(r) = -T \sum_{i=r+1}^{n} ln\left(1 - \lambda_i\right) \quad (3)$$

where: r is the number of co-integrating relationships between the variables. As in this case, the co-integration of the bivariate series with 1 relationship would imply one unit root. Here, T is the sample size. λ_i denotes the eigenvalues of matrix Π. If eigenvalues up to i

Table 9.3 Johansen procedure for co-integration test on logarithmic prices

	1 min	*5 min*	*15 min*	*30 min*	*1 hour*	*1 day*
Result	*Co-integrated*	*Co-integrated*	*Co-integrated*	*Co-integrated*	*Co-integrated*	*Co-integrated*
Trace Test						
r=0	144.5 ***	67.1***	63.2***	63.2***	66.4***	45.3***
Critical value 0.05 = 17.95, Critical Value 0.01 = 23.52						
r=>1	5.3	4.5	5.6	4.30	5.2	3.9
Critical value 0.05 = 8.18, Critical Value 0.01 = 11.65						
Lags	*14*	*8*	*8*	*7*	*5*	*2*
No. of Observations	*78,721*	*24,929*	*8,964*	*4,568*	*2,294*	*104*

Notes: The critical values applied for the test statistics are from Osterwald-Lenum (1992). Asterisks denote the following levels of significance: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. When determining the lags for the tests, the most parsimonious model specification used will be that identified by Akaike (AIC), Hannah-Quinn or Bayesian information criteria.

are $\lambda = 0$, then the rank of Π is zero and this is resulting to no co-integrating vectors. In this manner, the estimated eigenvalues of λ_o, λ_1,… λ_{n-1} would need to be significantly larger than the critical values for the rejection of the null hypothesis. The critical values are taken from Osterwald-Lenum (1992). As shown in Table 9.3, the null hypothesis of the zero co-integrating relationships (H_0: r = 0) can be rejected at all tested frequencies at the 1% critical value level, favouring the alternative hypothesis of 1 co-integrating relationship, (H_1: r > 0).

3.2 VAR/VECM processes

3.2.1 VAR model specification for Granger causality test

To assess the direction of causality, as well as the instances of robustness, the Granger causality test is applied to the bivariate time series. As the Granger causality model requires stationarity, the price series are accordingly transformed into returns. The ADF unit root test is applied for the series stationarity assessment. At all frequencies, the results show statistically significant stationarity at the 1% critical value level.

The Granger causality test involves identifying whether the lagged information of a variable Y provides any information about a variable X with also the lagged X components. The lags for this bivariate VAR process are determined with the shortest model, as identified by either AIC, HQ or BIC. To examine this, the F-test is applied to the unrestricted equation and restricted equation by ordinary least squares. Implying that Y_t does not Granger cause X_t, and in reverse, if $\beta = 0$, i.e: $H_o = \beta_1 = \beta_2 = \ldots = \beta_k = 0$. Should the F-test be greater than the critical value, then the null hypothesis of Y not Granger causing X, or in the reverse variable order, can be rejected.

3.2.2 Price discovery models

To measure price discovery as share of marketplaces' contribution of new information, this chapter employs the information share model by Joel Hasbrouck (1995) and the component share model by Gonzalo and Granger (1995). These are both widely used price discovery models and are constructed on the components of Vector Error Correlation Model (VECM).

As already confirmed under the Johansen cointegration test preparation, the VECM also requires non-stationary log prices. These price discovery models assume a single efficient market price, or long-term price equilibrium. Basing on the VECM short-term and long-term relationship components, these models can provide measurable insight into the futures and spot markets' lead–lag relationship.

The VECM model specification can be written as, in (4) where the change in the efficient price (ΔP_t) can be written:

$$\Delta P_t = \alpha(\beta' P_{t-1} - E(\beta' P_{t-1})) + \sum_{i=1}^{k} \Gamma_i \Delta P_{t-i} + \varepsilon_t \tag{4}$$

and:

$$\Pi = \alpha[\beta' P_{t-1} - E(\beta' P_{t-1})] \tag{5}$$

where: α is the error correction vector, containing the coefficients associated with the speed of adjustment of each price series to deviations from the equilibrium. The column β contains co-integrating vectors, or the long run coefficients. Considering that there are only two variables, here, Γ is a 2×2 common factor coefficient vector matrix. e_t is a 2×1 non-diagonal covariance matrix Ω of the residuals with a mean of zero. The matrix $\Pi = \alpha\beta'$ is of reduced rank in identifying co-integration. The model's common factor, or the efficient price, can be explained as the permanent component of I(1) co-integrated of vectors.

3.2.3 Information share

The information share (IS) model by Hasbrouck (1995) measures the proportion of the efficient price variance which can be attributed to each market's innovations. IS model incorporates the covariance matrix of innovations, the proportion of the random-walk variance that is attributed to the innovations in the spot or futures market price. Similar to the Johansen test (1991) before noting the futures and cash prices' integration of order I (1) with a random walk and the price changes, the VECM model can be transformed into a vector moving average of prices changes. Applying this model for a bivariate log prices:

$$\Delta P\mathrm{t} = \Psi(L)\varepsilon_t = \varepsilon_t + \Psi_1\varepsilon_{t-1} \ \Psi_2\varepsilon_{t-1} \tag{6}$$

where ΔP_t is change in the efficient price, $\psi(\mathrm{L})$ is a polynomial lag operator and ε_t the error term. Noting the Beverage–Nelson decomposition of the efficient price into permanent ($\psi(1)\varepsilon_t \sum_{s=1}^{t} \varepsilon_s$) and transitory ($\psi^*(L)\varepsilon_t$) components:

$$P_t = \psi^*(L)\varepsilon_t + \psi(1)\varepsilon_t \sum_{s=1}^{t} \varepsilon_s \tag{7}$$

The cumulate impacts of ε_t innovations are contained in the matrix $\psi(1)$ that measures the long-term impacts. Considering the Engle–Granger (1987) VECM representation theorem, the matrix $\psi(1)$ shows the following:

$$\beta'\psi(1) = 0 \text{ and } \psi(1)\alpha = 0 \tag{8}$$

and, further providing that:

$$\beta = (1, -1)' \tag{9}$$

The rows of $\psi(1)$ are identical as in Hasbrouck (1995). Vector $\psi = (\psi_1, \psi_2)$ is the common row vector of the moving average matrices $\psi(1)$. The definition of the permanent innovation $\psi'\varepsilon_t$ as the long-run impacts of innovations on each price series is as below:

$$\psi'\varepsilon_t = \psi_1\varepsilon_1,\text{t} + \psi_1\varepsilon_2,\text{t} \tag{10}$$

If Ω is diagonal, and the innovations are independent, the market i's (1 and 2) information share can be defined as below:

$$IS_i = \frac{\psi_i^2\Omega_i^2}{\psi\Omega\psi^T},\ i = 1,\ 2 \tag{11}$$

$\psi\Omega\psi^T$ is the variance of $\psi\varepsilon_t$. If Σ is non-diagonal and would not provide a unique solution, the market i's information share can be solved by applying Cholesky factorisation. Information share model is transformed into:

$$IS_i = \frac{\left(\left[\ \psi F\right]_i\right)^2}{\psi\Omega\psi'},\ i = 1,\ 2 \tag{12}$$

The F is the Cholesky decomposition of a lower triangular matrix of FF' = Ω.$[\psi F]_i$ is the *i* element of the matrix row. The IS result will depend on the ordering of the price variables, and as well as the general representations solved by Cholesky factorisation as upper and lower bounds. This in effect maximises the information share of market 1 whilst minimising market 2's share. Therefore, in this bivariate system, the marketplaces' information shares both require a combination of computed upper and lower bounds. As below:

$$IS_1 = \frac{\left(\psi_1\sigma_1 + \psi_2 p\sigma_1\right)^2}{\left(\psi_1\sigma_1 + \psi_2 p\sigma_2\right)^2 + \psi_2^2\sigma_2^2(1-p^2)},\ IS_2 = \frac{\psi_2^2\sigma_2^2(1-p^2)}{\left(\psi_1\sigma_1 + \psi_2 p\sigma_2\right)^2 + \psi_2^2\sigma_2^2(1-p^2)} \tag{13}$$

IS_1 and IS_2 represents the upper and lower bound of the marketplace. The average of upper and lower bound results of each market can be calculated as an estimation of price discovery measure (Baillie et al., 2002).

3.2.4 Component share

The component share (CS) model was introduced by Gonzalo and Granger (1995) with original examples sourced from macro finance and the purposes of researching long-running and co-integrated time series. Similarly to the IS, the CS model's common factor, or the efficient price, can be explained as the permanent component of I(1) co-integrated of vectors. However, the CS model differs by measuring the contribution to the efficient price from each market, where the contribution is defined as a function of the error correction coefficients of the marketplaces. The transitory components are not assumed to influence the common factor in the short run. Intuitively, this model places less price discovery share to a market where transitory activity is more prevalent. The CS model can be written as such:

$$P_t = f_t + G_t \tag{14}$$

$$f_t = \Gamma^T P_t = (\alpha^T_{\perp} \beta_{\perp})^{-1} \alpha^T_{\perp} P_t \tag{15}$$

$$\alpha_0 \perp \alpha = 0 \text{ and } \beta_0 \perp \beta = 0 \tag{16}$$

$$\Gamma^T = (\Gamma_1, \Gamma_2)^T = (\frac{\alpha_2}{\alpha_2 - \alpha_1}, \frac{\alpha_1}{\alpha_1 - \alpha_2})^T, \text{ i } = 1, 2 \tag{17}$$

Where: P_t is co-integrated prices and is composed of f_t, the long running component and G_t, the transitory component that has no permanent impact on the long run. $\alpha\perp$ is a vector that is orthogonal to the error correction coefficients matrix α for the market 1 and 2. α as well as β are VECM components. Γ^T is the common factor coefficient vector of sample T, which is the total sum of its components and is normalised to be equal to 1 (Harris et al., 2002).

The examination on price discovery measurement models by Ballie et al. (2002) assessed whether the price discovery should not only consider error correction processes but also correlations of VECM residuals, and suggested that inclusion of the latter in the model might offer more complete interpretations. In this manner, the information share test is assumed to be more comprehensive.

3.2.5 VAR/VECM process measurement limitations and robustness

The tests were performed at different frequencies for robustness purposes due to the possible auto-correlation features of intra-day data and also for Bitcoin's price volatility against the US dollar. The expectation is that when using intra-day data, the samples will exhibit positive autocorrelation in the residuals. Further the Durbin–Watson test is applied to log prices to measure the linear regression before lags are applied in preparation for the VECM test. The Durbin–Watson test can be facilitated to identify the prevalence of continuing price increases or decreases which could be related to momentum investing. Momentum trading would need to be separated from liquidity induced price increase and decrease moves as not all momentum trading can be explained by irrational trading or trading frictions as suggested by an equity return research (Johnson, 2002).

The value of the Durbin–Watson test lies between the range of 0 and 4. Small values of the estimations indicate that the consecutive error terms are positively correlated. The test estimations as shown in Table 9.4 showed positive autocorrelation on the higher frequency intra-day data on the time series' co-integration. A result between the 0 and 1 value can be identified as noting positive autocorrelation in the series as a rule-of-thumb. This was the range in which all the tested intra-day results were estimated to belong. To make the log prices applicable for the VEC model, the lags were defined with AIC, HQ and BIC methods.

Additionally, taking into account of the high levels of volatility of the asset that can be identified in Table 9.1, additional tests of heteroscedasticity were conducted on the VAR transformed returns with White's test. White's test was preferred due to its non-parametric testing robustness. The return series were both transformed with EGARCH(1.1), IGARCH(1.1) adjustments. Also, NAGARCH(1.1) adjustments were trialled with the same specifications, but this would not give a solution on all frequencies. The results can be seen in Table 9.5. It is worth noting that these GARCH based models have not been specifically designed for intra-day data. Subsequently, the volatility adjusted continued to show heteroscedasticity at the intra-day frequencies. Only the daily returns, expectedly, were identified

Table 9.4 Durbin-Watson test statistics for the linear regression of log prices

	1 min	*5 min*	*15 min*	*30 min*	*1 hour*	*1 day*
Test statistics	0.10***	0.27***	0.45***	0.64***	0.90***	1.85
P-value	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.193)
Lags to be applied	*14*	*8*	*7*	*7*	*5*	*2*
No. of Observations	*78,721*	*24,929*	*8,964*	*4,568*	*2,294*	*104*

Notes: Asterisks denote the following levels of significance: *** p<0.01, ** p<0.5, * p<0.1. P-values are in the parentheses.

Table 9.5 White's test for heteroscedasticity of VAR on returns

	1 min	*5 min*	*15 min*	*30 min*	*1 hour*	*1 day*
Exponential GARCH	0	0	0	0	0	0.514
	(1012.4)	(10507.8)	(2546.6)	(260.6)	(182.6)	(23.1)
Integrated GARCH	0	0	0	0	0	0.228
	(2044.3)	(5835.9)	(2400.7)	(311.1)	(196.8)	(28.8)
Lags	*14*	*9*	*8*	*7*	*5*	*2*
No. of Observations	*78,720*	*24,928*	*8,963*	*4,567*	*2,293*	*103*

Notes: White's test is applied to log returns VAR transformation. This T-test formalises the hypothesis of H0: Homoscedasticity and H1: Heteroscedasticity. Asterisks denote the following levels of significance: *** p<0.01, ** p<0.5, * p<0.1. Test shows P-values and test results in parenthesis. Sample time period 2017.12.13 to 2018.05.16 (UCT)

as homoscedastic after EGARCH and IGARCH adjustments. Continuing, and also frequent change in the Bitcoin market variance, can be assumed at intra-day frequency data. This might be due to the frequent market news and actions, and the Bitcoin market sensitivity to these due to the lack of traditional fundamentals, and noise-based momentum trading.

4 The empirical results and estimations

Bitcoin spot and futures pertain to the same underlying asset and were correspondingly identified to be co-integrated by applying the Johansen Co-integration Trace test to the time series' logarithmic intra-day prices at different frequencies. At the 1-minute frequency, the CBOE futures and spot prices show Johansen trace statistics of 144.5 with 5% critical values of 17.95 and 1% critical values of 23.5. This makes the researched bivariate series I(1) co-integrated at all the tested frequencies.

To research this relationship in detail with regards to predicting the move of a variable from another variable move, the Granger causality test was employed onto the transformed returns. The test results that can be seen in Table 9.6 demonstrate significant p-value statistics of the futures Granger causing spot returns at all frequencies and for spot market Granger causing the futures at the 1-minute frequency level. The lower frequencies do not reveal significant results of the spot index Granger causing the futures returns. The Granger causality test shows that the relationship cannot be ascertained to be bidirectional at lower frequencies while futures exhibit Granger causing spot markets at all tested frequencies.

The VECM is applied to non-stationary log prices for the Bitcoin index and CBOE futures at different frequencies. The results in Table 9.7 show an error correction coefficient that is significant at 1% p-value level for the futures impacting the index prices in all the frequency samples. The VECM results show insignificant error correction test results of futures correcting towards the efficient price at all frequencies. In contrast the spot market was found to be correcting toward the efficient price with statistical significance on all frequencies. Spot market is also shown to be downwardly correcting to the efficient price.

Table 9.6 Granger causality – null hypothesis p-value – returns

	1 min	*5 min*	*15 min*	*30 min*	*1 hour*	*1 day*
Spot does not Granger cause Futures	0.000	0.300	0.270	0.106	0.385	0.259
-``- IGARCH adj.	0.000	0.000	0.168	0.348	0.857	0.230
-``- EGARCH adj.	0.000	0.000	0.062	0.159	0.723	0.328
Futures does not Granger cause Spot	0.000	0.000	0.000	0.000	0.000	0.000
-``- IGARCH adj.	0.000	0.000	0.000	0.000	0.000	0.000
-``- EGARCH adj.	0.000	0.000	0.000	0.000	0.000	0.000
Lags	*14*	*9*	*8*	*7*	*5*	*2*
Observations	*78,720*	*24,928*	*8,963*	*4,567*	*2,293*	*103*

Notes: When determining the lags for the tests, the most parsimonious model specification will be used by identified by either Akaike (AIC), Hannah-Quinn or Bayesian information criteria. Time period 2017.12.13 to 2018.05.16 (UCT)

Table 9.7 Vector error correction model results – log prices

	1 min	*5 min*	*15 min*	*30 min*	*1 hour*	*1 day*
Error Correction Term						
SPOT	−0.008***	−0.030***	−0.046***	−0.099***	−0.191***	−0.808***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.807)
FUTURES	0.002	0.038	-0.000	-0.016	-0.038	0.193
	(0.283)	(0.713)	(0.989)	(0.545)	(0.454)	(0.548)
Cointegration Relations	0.989	0.989	0.991	0.991	0.990	1.010
Correlation of Residuals	0.753	0.806	0.866	0.887	0.907	0.899
Residual Standard Error						
SPOT	0.002	0.004	0.007	0.010	0.015	0.056
FUTURES	0.003	0.005	0.008	0.011	0.016	0.058
% Adjusted R^2						
SPOT	20.5%	19.9%	13.5%	12.3%	11.9%	22.8%
FUTURES	0.3%	2.1%	5.1%	0.5%	0.6%	6.7%
Lags	*14*	*8*	*7*	*7*	*5*	*2*
Observations	*78,721*	*24,929*	*8,964*	*4,568*	*2,294*	*104*

Notes: Asterisks denote the following levels of significance: *** p<0.01, ** p<0.5, * p<0.1. P-values are in the parentheses.

Table 9.8 Information share and component share estimations – log prices

	1 min	*5 min*	*15 min*	*30 min*	*1 hour*	*1 day*
IS upper bound						
FUTURES	34.1%	31.6%	23.3%	27.7%	24.8%	13.1%
INDEX	65.9%	68.4%	76.7%	72.6%	75.2%	86.9%
IS lower bound						
FUTURES	99.1%	99.9%	99.9%	99.5%	99.2%	99.4%
INDEX	0.9%	0.1%	0.1%	0.5%	0.8%	0.6%
Average IS						
FUTURES	66.6%	65.8%	73.3%	63.4%	62.0%	56.3%
INDEX	33.4%	34.2%	26.7%	36.6%	38.0%	43.7%
Component share						
FUTURES	82.3%	93.1%	95.0%	87.6%	84.2%	81.6%
INDEX	17.7%	6.9%	5.0%	12.4%	15.8%	18.4%
Lag	*14*	*8*	*8*	*7*	*5*	*2*
Observations	*78,721*	*24,929*	*8,964*	*4,568*	*2,294*	*104*

Notes: The information share (IS) model is by Hasbrouck (1995). The component share (CS) model is by Gonzalo and Granger (1995). When determining the lags for the tests, the most parsimonious model specification will be used by identified by either Akaike, Hannah-Quinn or Bayesian information criteria.

Both IS and CS models measure each market's price discovery contribution as a share of the total 100% price formation. Table 9.8 shows the results of these models. At 1-minute level frequency, 66.6% of price discovery is generated from the futures market as measured by the averaged IS model and 82.3% as measured by CS model. At 1-hour frequency level, the IS result is 62% and the CS result is 84.2% of the price discovery share for the futures market. The futures dominate the price discovery at all sampled frequencies with a range from 56% to 73% with information share test and respectively 82% to 95% with component share test. The results from Granger causality and VECM corroborate the information share and component share model estimations with supporting that the futures are leading the spot market in price discovery.

5 Concluding remarks

The analysis of the Bitcoin spot-futures information share and component share test results suggest that the Bitcoin futures are leading the price discovery. These findings are also corroborated by the results from VAR and VECM specified processes. The results support the majority of research findings of futures' dominance in price discovery. As the component share model does not consider the transitory element, the higher information share result may imply more prevalent noise trading in the spot market. Due to the comparatively low volumes in the futures trading of this asset, this will not support wider participation among institutional traders in the whole marketplace. Nevertheless, even with the unusually high margins, the Bitcoin futures provide traders a more robust instrument and more efficient information for trading in the developing but frictional Bitcoin marketplace. The challenge for the Bitcoin market is to improve the undeveloped best practises among the Bitcoin cash exchanges that largely remain unregulated and mainly retail focused.

Notes

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2 F.A. Hayek interview at the University of Freiburg in 1984 https://www.youtube.com/watch?v=EYhEDxFwFRU&feature=emb_logo
3 Milton Friedman interview by National Taxpayers Union in 1999 https://www.youtube.com/watch?v=j2mdYX1nF_Y
4 Bitcoinity.org, which is a data provider about cryptocurrencies stores information about the technical difficulty with mining.
5 CME and CBOE futures, source: Thomson Reuters and Coinmarketcap.com. January 2018.
6 This study considers an ititutional investor as an entity that manages funds, for instance, for a pension fund or an insurance company. Retail trading in Bitcoin, on the other hand, might involve mobile phone interface with a Bitcoin exchange with access to very limited trading information.
7 For instance, on 7 March 2018, CME offered Gold futures with 100 troy ounce contracts with a maintenance margin of US$3500. 100 troy ounce of gold was reported to be US$1330.0 making the leverage 38 times.
8 Bitcoin Ban Expands Across Credit Cards as Big U.S. Banks Recoil, Bloomberg, 2 February 2018.
9 Bitflyer Lighting FX, accessed on 30 January 2018.
10 E.g. Bitcoinity Bitcoin Arbitrage Chart
11 Twitter: history of Bitcoin exchange downtimes may be seen on the Twitter, where users of Bitcoin exchanges can share and seek information from peers about exchange downtimes and possibly interact with exchanges themselves.
12 Coindesk Bitcoin Price Index simple average weighted constituents of immediate bid and offer spread are Bitstamp, Coinbase/GDAX, itBit, Bitfinex as of 31 May 2018. The time frequency is 1-minute UTC time.
13 Data Availability Statement – data subject to third party restrictions: Futures data are available at https://www.cboe.com with the permission of Cboe Global Markets, Inc.
14 CBOE Bitcoin futures trading hours are 3:30 p.m. to 3:15 p.m. CT on Mondays and 8:30 a.m. to 3:15 p.m. Tuesday through Friday. Weekend related extended hours are 5 p.m. Sunday to 8:30 a.m. Monday.
15 The time stamp matching is important, as Garbade and Silber (1983) find. Daily cut off pricing point can either make the market appear more dominant with only 30 minutes difference in the timing.
16 The study utilizes R for analysis. For more on R model implementations see Pfaff (2008).

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