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The development of Bitcoin futures: Exploring the interactions between cryptocurrency derivatives

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ABSTRACT

We utilise a high-frequency analysis to investigate the period surrounding the establishment of two new futures contracts based on the performance of Bitcoin. Our analysis shows that there have been significant pricing effects sourced from both fraudulent and regulatory unease within the industry. While analysing breakpoints in efficiency, we verify the view that Bitcoin futures dominate price discovery relative to spot markets. However, we add to this research by finding that CBOE futures are found to be the leading source of informational flow when compared directly to their CME equivalent.

1. Introduction

To date, cryptocurrency research has developed substantially since the product's creation ten years ago. So far, Bitcoin has been identified to contain pricing inefficiencies (Urquhart, 2016; Sensoy, 2019; Mensi et al., 2019; Corbet et al., 2019a), to be in isolation from other traded assets (Corbet et al., 2018c), to present evidence of price clustering (Urquhart, 2017), pricing bubbles (Corbet et al., 2018b), regulatory ambiguity (Fry, 2018), and exceptional levels of both complex and uncomplex fraud (Gandal et al., 2018). Although development and innovation within financial markets is of course associated with some risk, due to the exceptional number of relatively illicit activity within the product's pricing, trading techniques and indeed the exchanges on which it trades, the product's development has continued at pace, despite the exceptional pricing volatility that has taken place (Katsiampa, 2017; Katsiampa et al., 2019)[1].

One such event, widely observed as a significant milestone in the development of cryptocurrencies as an investment product, was the initiation of Bitcoin futures. The trading of futures contracts on Bitcoins commenced at the Chicago Mercantile Exchange (CME) and the Chicago Board Options Exchange (CBOE) in December 2017. Nevertheless, the literature on Bitcoin futures markets is limited. In our study, three aspects of the introduction of futures on the spot market will be explored. Firstly, the presence of breakpoints in the data series is examined. Secondly, we utilise two separate Bitcoin futures exchanges to identify their price

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[1] A concise overview of associated cryptocurrency literature was developed by Corbet et al. (2019b).

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Table 1
Stylised facts based on Cboe and CME Bitcoin Futures.

Variable	CBOE Futures	CME Futures
Product Code	XBT	BTC
First Traded	10th of December 2017	18th of December 2017
Contract unit	1 Bitcoin	5 Bitcoins
Tick Size	The CBOE minimum tick for a directional non-spread trade is 10 points or $10. A spread tick has a tick size of $0.01.	The tick value at CME is $5 per Bitcoin. This means that the price movement for a single contract will move in increments of $5 and amounts to a total of $25 per contract.
Underlying Spot Price	CBOE will price contracts with a single auction at 4 pm on the final settlement date. It will use Bitcoin prices from the Gemini exchange	CME contracts are based on the Bitcoin Reference Rate (BRR) index, which aggregates Bitcoin trading activity across four Bitcoin exchanges, itBit, Kraken, BitStamp, and GDAX, between 3pm and 4pm GMT.
Position Limits	A person: (i) may not own or control more than 5000 contracts net long or net short in all XBT futures contract expirations combined and (ii) may not own or control more than 1000 contracts net long or net short in the expiring XBT futures contract, commencing at the start of trading hours 5 business days prior to the Final Settlement Date of the expiring XBT futures contract.	1000 contracts with a position accountability level of 5000 contracts.
Price Limits	XBT futures contracts are not subject to price limits.	7% above and below settlement price, +/-13% previous settlement, +/-20% for prior settlement.
Settlement	The Final Settlement Value of an expiring XBT futures contract shall be the official auction price for Bitcoin in U.S. dollars determined at 4:00 p.m. Eastern Time on the Final Settlement Date by the Gemini Exchange Auction.	Cash settled by reference to Final Settlement Price.

discovery relationship with spot markets. Finally, we analyse the dynamic transmission of information flows between these new cryptocurrency futures markets. This is therefore the first study to explore the two futures markets.

2. Data

Both the CME and the CBOE future contracts are cash settled in US Dollars where data is obtained at a one-minute frequency from Tick Data LLC, and Bitcoin price data from Thomson Reuters Eikon. Table 1 displays contract information for these two new futures contracts, while Table 2 presents the descriptive statistics of each of the Bitcoin series used. We clearly observe the key differences with regards to the ticks sizes of both contracts along with the differing indices that are used to determine the official pricing structure. This is among one of the key issues that have been identified with the two types of new product, namely the lack of underlying uniformity with further issues identified within the strict price limits which were sets at 20% above of below the reference price to reduce the transmission of exceptional volatility to futures markets. Further worries have been relayed about the potential for systemic risk sourced in the new futures products and the instability of the new products sourced in the lack of regulation and sharp volatility.

From the one-minute transaction prices we calculate the log return for each period, presented with an associated histogram of returns in Fig. 1, representing the sample period that includes 63,659 observations between 18 December 2017 and 26 February 2018. Fig. 2 presents evidence of the differences between both pricing and liquidity of the two futures market products. We remove spot Bitcoin trading data during the closure of the Bitcoin futures markets for synchronicity. To generate robustness in our selected methodology, the analysis is replicated again at 5-, 10-, 15-, 20-, 30- and 60-min windows of investigation.

Figs. 3 and 4 represent some key differences between the existing CBOE and CME Bitcoin futures products. Although we observe clear similarities in basis behaviour there have been episodes of substantial price variation between both futures products. Further,

Table 2
Descriptive Statistics for both prices and returns of Bitcoin spot and futures markets.

	Spot Bitcoin		CME Bitcoin		CBOE Bitcoin	
	Price	Return	Price	Return	Price	Return
Mean	11,991.03	−0.00001	12,034.52	−0.00001	12,065.13	−0.00001
Median	11,275.36	0.00000	11,285.00	0.00000	11,320.00	0.00000
Standard Deviation	2936.43	0.00280	2976.31	0.00269	2970.62	0.00284
Sample Variance	8,622,480	0.00001	8,858,284	0.00001	8,824,422	0.00001
Kurtosis	−0.65532	77.20488	−0.49224	35.35072	−0.53587	21.67577
Skewness	0.37537	−1.21273	0.46672	−0.11950	0.44057	−0.14234
Minimum	$5924.72	−0.11218	$6020.00	−0.06560	$6000.00	−0.06528
Maximum	$19,215.86	0.07509	$19,840.00	0.05818	$19,790.00	0.05787
Time of Minimum Price	06/02/2018, 07:59		06/02/2018, 02:58		06/02/2018, 02:59	
Time of Maximum Price	18/12/2017, 12:09		18/12/2017, 07:02		18/12/2017, 07:06	

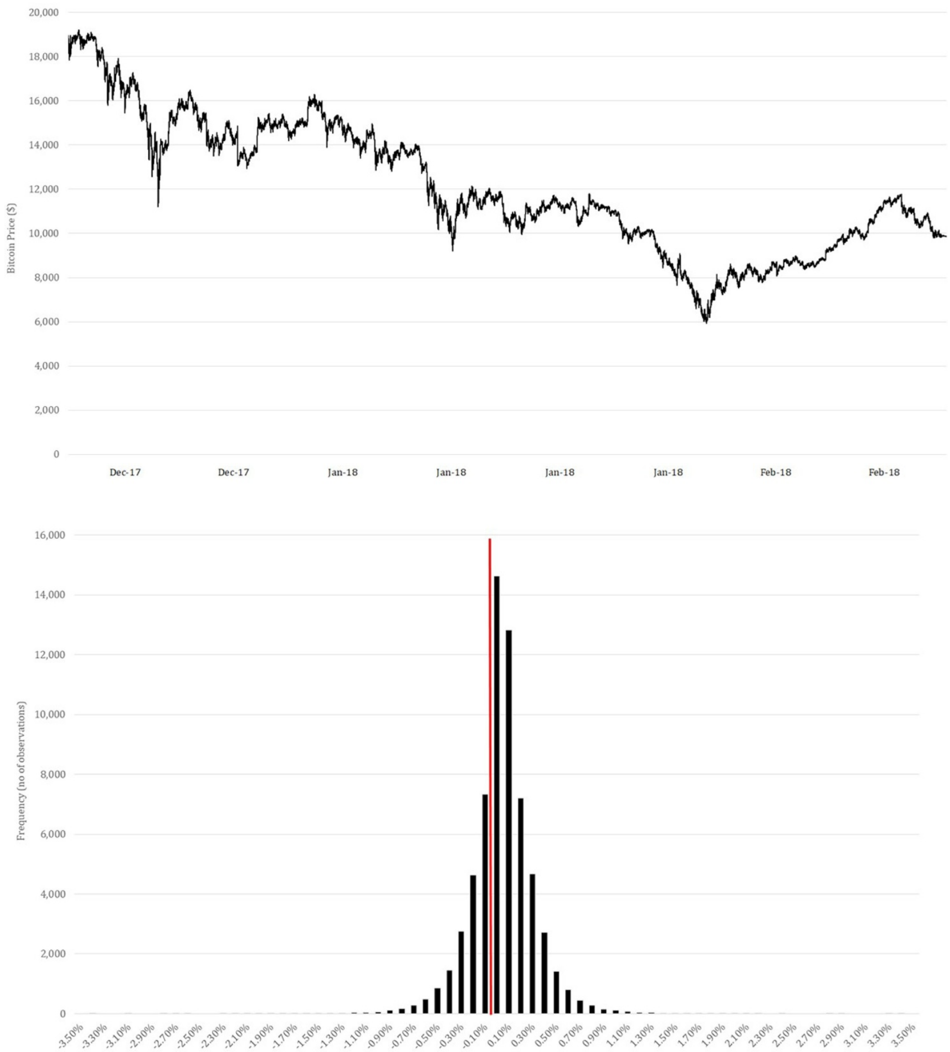

Fig. 1. Bitcoin Spot Market Performance. Note: The above figure presents the performance and histogram of returns for Bitcoin spot prices in the three month periods after the initiation of trading in CME and CBOE futures contracts.

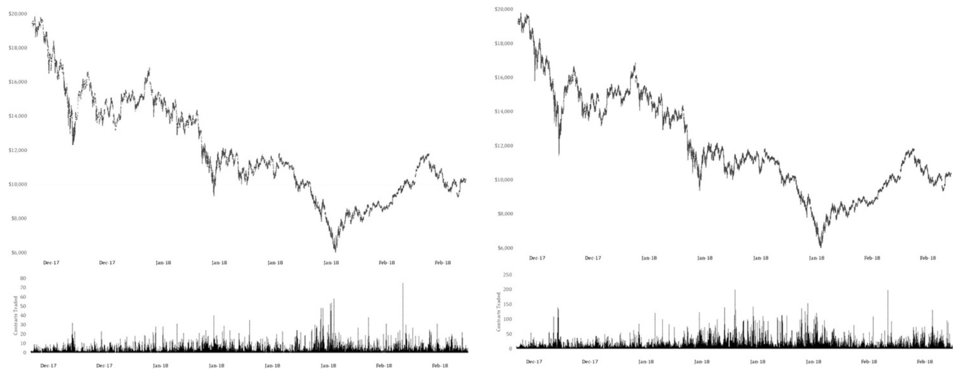

Fig. 2. Comparing CME and CBOE Bitcoin future's prices and liquidity. Note: The above figure presents the price and liquidity for CME Bitcoin futures in the left-hand panel and CBOE Bitcoin futures in the right-hand panel.

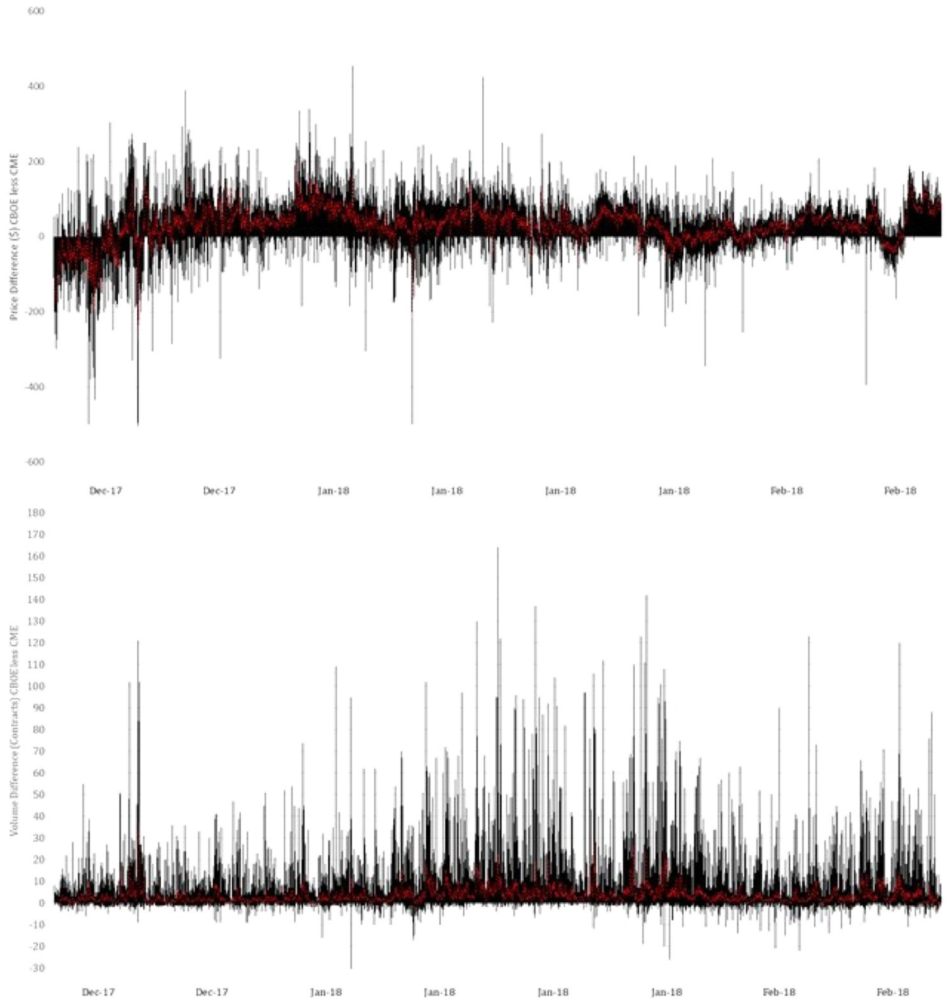

Fig. 3. Differences in CME and CBOE Bitcoin future's prices and liquidity. Note: The above figure presents the difference in price (top-panel) and liquidity (bottom-panel) for CME Bitcoin futures and CBOE Bitcoin futures.

CBOE presents evidence of consistently elevated trading volumes when compared to similar CME products, however, a CBOE contract unit is worth only 1BTC, while a CME contract is worth 5BTC.

3. Analysis

Our empirical analysis begins with performing the Augmented Dickey-Fuller (ADF) unit root tests in order to investigate the stationarity of the price returns. The results (presented in Table 3) confirm the stationarity of the return series of the spot as well as of the two futures markets. However, since the period under examination could be unstable, we also test for stability by performing Sequential Bai-Perron (Bai, 1997; Bai and Perron, 1998) tests. In doing so, we use a trimming percentage of 0.15, allow for up to five unknown breakpoints and for error distributions to differ across breaks, after fitting an Autoregressive (AR) model with a constant to the series, while selecting the lag order according to the statistical significance of the estimated parameters, as in Göktaş and Dişbudak (2014), among others. We also allow for both the constant and the AR terms to vary across breakpoints. In order to confirm the results from the Sequential Bai-Perron tests found in Table 4, the Chow test is also performed when a structural break is detected by the Bai-Perron tests.

When analysing the three different series at a one minute frequency, we observe a variety of structural breaks while using the AR methodologies. The Bitcoin spot market presents evidence of a breakpoint at 18:43 on 24 December 2017. This coincides towards the end of two extraordinarily disruptive days of trading, where as the value of Bitcoin sharply collapsed, trading was halted on a number of exchanges due to technical issues associated with high volumes and an absence of liquidity in certain situations. The CBOE futures market presents two separate breakpoints, with the first at 09:01 on 5 January 2017, coinciding with a sharp collapse in the price of Ripple which reverberated throughout cryptocurrency markets, but also with a decision taken by Visa to suspend payment cards cards run by BitPay, Cryptopay and Bitwala all so as to return funds to users. This was observed as an exceptionally damaging event

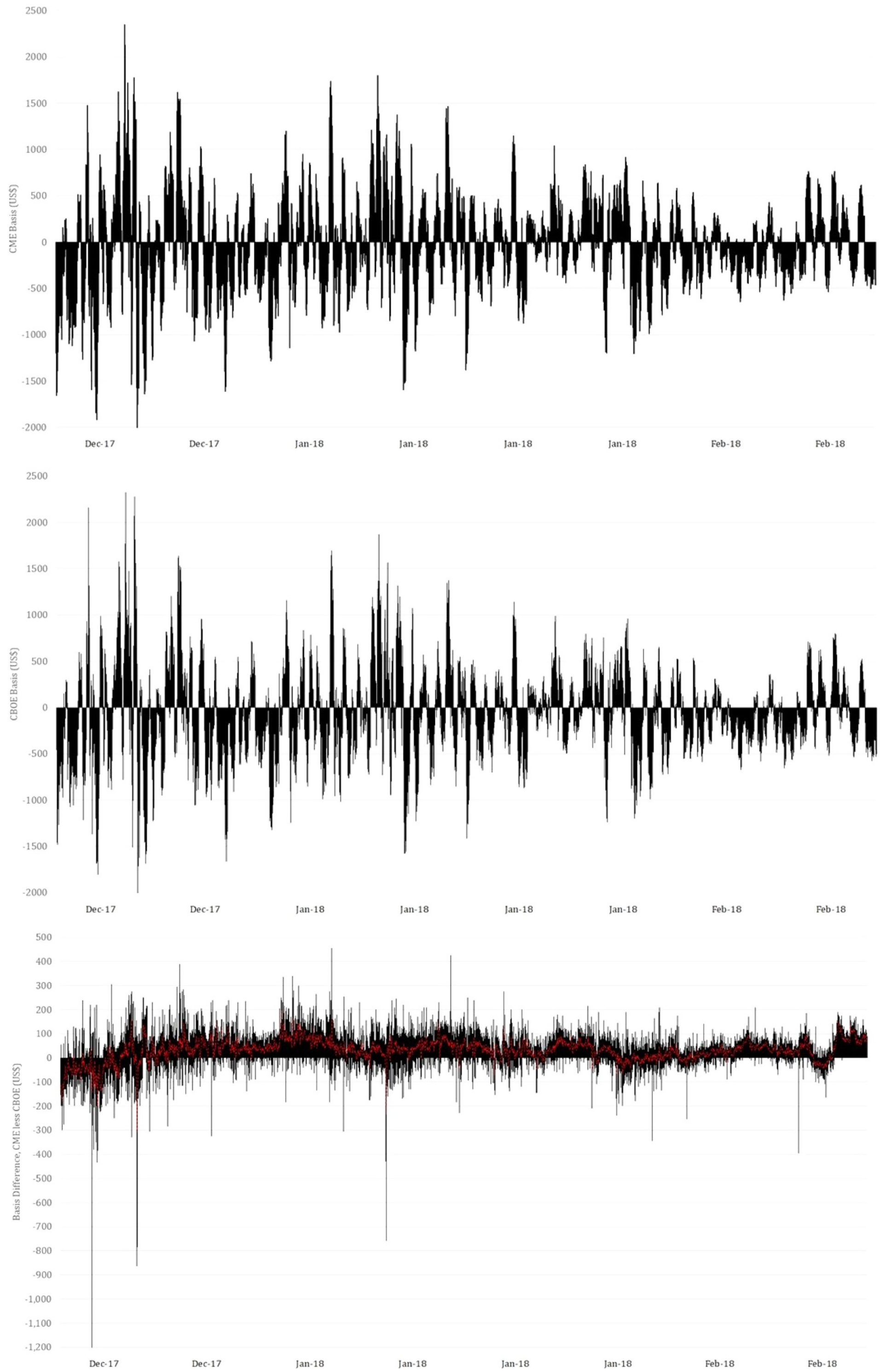

Fig. 4. Basis and difference in CME and CBOE Bitcoin futures basis. Note: The above figure presents the difference in the basis of Bitcoin futures traded on the CME (top-panel) and the CBOE (middle-panel). The bottom-panel presents the difference in the basis levels as measured by CME futures less CBOE futures.

reputationally for cryptocurrencies at large. The second CBOE breakpoint occurred at 12:33 on 17 January 2018, on the same day as the sole breakpoint of the CME time series also occurs on 17 January 2018, but later in the day at 19:16. This latter breakpoint is significant. At the same time, there appears to have been multiple regulatory announcements, where the SEC stated categorically that

Table 3
Unit root tests.

	ADF		KPSS	
	Prices	Returns	Prices	Returns
Spot				
1-min	−2.2776	−261.6619***	702.1772***	0.0286
5-min	−2.2514	−117.3774***	140.2949***	0.0300
10-min	−2.2534	−83.7027***	69.9882***	0.0297
15-min	−2.2550	−67.3051***	46.8509***	0.0325
30-min	−2.1819	−47.6093***	23.2955***	0.0343
60-min	−2.0125	−34.8915***	11.8440***	0.0367
CME				
1-min	−2.3821	−182.0275***	715.3175***	0.0309
5-min	−2.3729	−83.3034***	142.9976***	0.0323
10-min	−2.3691	−84.8046***	71.2818***	0.0326
15-min	−2.3730	−66.9666***	47.6835***	0.0345
30-min	−2.3745	−44.5734***	23.6998***	0.0369
60-min	−2.4504	−34.6409***	12.0810***	0.0342
CBOE				
1-min	−2.3355	−152.7438***	712.2056***	0.0284
5-min	−2.3433	−84.7437***	142.4023***	0.0315
10-min	−2.3276	−85.6780***	71.0163***	0.0323
15-min	−2.3491	−67.3985***	47.4798***	0.0352
30-min	−2.3829	−45.6538***	23.5968***	0.0379
60-min	−2.4075	−33.9954***	12.0568***	0.0365

Note: *** denotes significance at 1%. ADF (KPSS) test checks for the null hypothesis of non-stationarity (stationarity). According to both test results, return series are stationary, however price series are not.

Table 4
Breakpoint tests.

	Lag	Bai-Perron test Scaled F-statistic	Break date	Chow test F-statistic
Spot returns				
1-min	1	27.09721***	12/24/2017 18:43	54.24632***
5-min	1	4.561002	None	
10-min	1	6.738106	None	
15-min	0	6.915871	None	
30-min	0	7.519217*	1/17/2018 22:00	5.436195**
60-min	1	8.295613	None	
CME returns				
1-min	3	30.26649***	1/17/2018 19:16	11.66304***
5-min	2	14.99862**	1/19/2018 13:25	3.905064***
10-min	1	16.17580***	1/19/2018 09:10	6.366341***
15-min	0	7.201381*	1/17/2018 23:30	5.961818**
30-min	2	12.01455	None	
60-min	2	9.265328	None	
CBOE returns				
1-min	3	21.24460**	1/05/2018 09:01	54.38687***
			1/17/2018 12:33	19.47174***
5-min	2	10.06130	None	
10-min	1	10.16419*	1/17/2018 20:50	5.607146***
15-min	0	7.580405*	1/17/2018 23:30	6.095687**
30-min	0	7.804163*	1/17/2018 17:00	6.608568**
60-min	2	11.37750	None	

Note: *, ** and *** denote significance at 10%, 5% and 1% levels, respectively. We allow up to a maximum number of 5 break points and employ a sequential test to determine the exact number of break points in the series.

they possessed substantial regulatory fears about cryptocurrency-based investments and funds, asking thirty-one specific questions as to how funds managers and ETFs would support and underwrite such, while raising further questions about how one could mitigate the possible risks of market manipulations. This news arrived as Bitcoin prices were falling rapidly from their recently achieved values above $19,215. Further issues with regards to fraud and regulatory capacity amplified observed market unease. However, as further evidence of the development and advancement of these new derivatives, there is evidence in the presented breakpoints of efficiency within the pricing structures of both CME and CBOE futures products.

While advancing understanding about the pricing behaviour of both Bitcoin spot and futures assets, we must also establish and develop the interrelationships in information flows and price discovery between these new assets. We therefore utilise two standard measures of price discovery commonly employed in the literature: the Hasbrouck (1995) Information Share (IS) and the Gonzalo and Granger (1995) Component Share (CS) measure. Hasbrouck (1995) demonstrates that the contribution of a price series to price discovery (the 'information share') can be measured by the proportion of the variance in the common efficient price innovations that is explained by innovations in that price series. Gonzalo and Granger (1995) decompose a cointegrated price series into a permanent component and a temporary component using error correction coefficients. The permanent component is interpreted as the common efficient price, the temporary component reflects deviations from the efficient price caused by trading fractions. We estimate IS and CS, as developed by Hauptfleisch et al. (2016) using the error correction parameters and variance-covariance of the error terms from the Vector Error Correction Model (VECM):

$$\Delta p_{1,t} = \alpha_1(p_{1,t-1} - p_{2,t-1}) + \sum_{i=1}^{20} \gamma_i \Delta p_{1,t-i} + \sum_{j=1}^{20} \delta_j \Delta p_{2,t-j} + \varepsilon_{1,t} \tag{1}$$

$$\Delta p_{2,t} = \alpha_2(p_{1,t-1} - p_{2,t-1}) + \sum_{k=1}^{20} \varphi_k \Delta p_{1,t-k} + \sum_{m=1}^{20} \phi_m \Delta p_{2,t-m} + \varepsilon_{2,t} \tag{2}$$

where $\Delta p_{i,t}$ is the change in the log price ($p_{i,t}$) of the asset traded in market i at time t. The next stage is to obtain the component shares from the normalised orthogonal coefficients to the vector of error correction, or:

$$CS_1 = \gamma_1 = \frac{\alpha_2}{\alpha_2 - \alpha_1}; \; CS_2 = \gamma_2 = \frac{\alpha_1}{\alpha_1 - \alpha_2} \tag{3}$$

Given the covariance matrix of the reduced form VECM error terms[2] where:

$$M = \begin{pmatrix} m_{11} & 0 \\ m_{12} & m_{22} \end{pmatrix} = \begin{pmatrix} \sigma_1 & 0 \\ \rho\sigma_2 & \sigma_2(1-\rho^2)^{\frac{1}{2}} \end{pmatrix} \tag{4}$$

we calculate the IS using:

$$IS_1 = \frac{(\gamma_1 m_{11} + \gamma_2 m_{12})^2}{(\gamma_1 m_{11} + \gamma_2 m_{12})^2 + (\gamma_2 m_{22})^2} \tag{5}$$

$$IS_2 = \frac{(\gamma_2 m_{22})^2}{(\gamma_1 m_{11} + \gamma_2 m_{12})^2 + (\gamma_2 m_{22})^2} \tag{6}$$

Recent studies show that IS and CS are sensitive to the relative level of noise in each market, they measure a combination of leadership in impounding new information and the relative level of noise in the price series from each market. The measures tend to overstate the price discovery contribution of the less noisy market. An appropriate combination of IS and CS cancels out dependence on noise (Yan and Zivot, 2010; Putniņš, 2013). Information leadership is derived by Yan and Zivot (2010) to measure as to which price series leads the process of adjusting to innovations in the fundamental value. It is best described as:

$$IL_1 = \left| \frac{IS_1}{IS_2} \frac{CS_2}{CS_1} \right| \text{ and } IL_2 = \left| \frac{IS_2}{IS_1} \frac{CS_1}{CS_2} \right| \tag{7}$$

The combined measure is known as the Information Leadership Share (ILS) which is calculated as:

$$ILS_1 = \frac{IL_1}{IL_1 + IL_2} \text{ and } ILS_2 = \frac{IL_2}{IL_1 + IL_2} \tag{8}$$

We estimate all four price discovery metrics, noting that they measure different aspects of price discovery. The results in Table 5 show that both of the analysed futures markets lead in the price discovery of Bitcoin spot prices across all metrics and frequencies analysed in the immediate aftermath of the introduction of Bitcoin futures. In contrast to results based on a shorter period as in Corbet et al. (2018a), it appears that as the new cryptocurrency futures markets developed, they presented substantial leadership in price discovery over spot Bitcoin markets. This relationship is found to somewhat diminish as data of a lower frequency is analysed. While it was assumed that the concentration of price discovery in the initial months of trade was sourced as a function of novelty, there is much evidence to suggest that this novelty diminished over time. This supports both the views of Bohl et al. (2011) and Corbet et al. (2018a), primarily that there appears to have been a dominant presence of unsophisticated investors in these futures markets, which overwhelmed the price discovery process. But this has now changed, particularly as sophisticated institutional investors entered the market. We must point out that there is a substantial difference in the source of price discovery when separated by CME and CBOE futures price discovery. We clearly observe that when analysing the IS and CS metrics, CBOE Bitcoin futures account for over 70% of the information affecting CME Bitcoin futures. However, the strength and direction of this relationship reverses quite substantially when analysing IL and ILS. Within this context, we identify that the transmission of pricing discovery effects from CBOE to CME is most likely associated with the differing contract sizes of each, resulting in a substantially larger number of contracts traded

[2] $\Omega = \begin{pmatrix} \sigma_1^2 & \rho\sigma_1\sigma_2 \\ \rho\sigma_1\sigma_2 & \sigma_2^2 \end{pmatrix}$ and its Cholesky factorisation, $\Omega = MM'$.

Table 5
CME and CBOE pice discovery results.

Frequency	1-min		5-min		10-min	
BTC Spot vs BTC CME	Spot	BTC CME	Spot	BTC CME	Spot	BTC CME
IS (Hasbruck)	0.0286	0.9714	0.0230	0.9770	0.0407	0.9593
CS (Gonzalo)	0.1326	0.8674	0.1395	0.8605	0.1861	0.8139
IL (Yan)	0.1926	5.1914	0.1450	6.8949	0.1855	5.3908
ILS (Putnins)	0.0358	0.9642	0.0206	0.9794	0.0333	0.9667
BTC Spot vs BTC CBOE	Spot	BTC CBOE	Spot	BTC CBOE	Spot	BTC CBOE
IS (Hasbruck)	0.0245	0.9755	0.0468	0.9532	0.0430	0.9570
CS (Gonzalo)	0.1293	0.8707	0.1999	0.8001	0.1970	0.8030
IL (Yan)	0.1695	5.8991	0.1966	5.0871	0.1834	5.4528
ILS (Putnins)	0.0279	0.9721	0.0372	0.9628	0.0325	0.9675
BTC CME vs BTC CBOE	BTC CME	BTC CBOE	BTC CME	BTC CBOE	BTC CME	BTC CBOE
IS (Hasbruck)	0.2919	0.7081	0.4072	0.5928	0.4630	0.5370
CS (Gonzalo)	0.2766	0.7234	0.2747	0.7253	0.3539	0.6461
IL (Yan)	1.0783	0.9274	1.8131	0.5515	1.5746	0.6351
ILS (Putnins)	0.5376	0.4624	0.7668	0.2332	0.7126	0.2874
Frequency	**15-min**		**30-min**		**60-min**	
BTC Spot vs BTC CME	Spot	BTC CME	Spot	BTC CME	Spot	BTC CME
IS (Hasbruck)	0.0298	0.9702	0.0421	0.9579	0.0851	0.9149
CS (Gonzalo)	0.1569	0.8431	0.2036	0.7964	0.3277	0.6723
IL (Yan)	0.1650	6.0604	0.1719	5.8161	0.1909	5.2391
ILS (Putnins)	0.0265	0.9735	0.0287	0.9713	0.0352	0.9648
BTC Spot vs BTC CBOE	Spot	BTC CBOE	Spot	BTC CBOE	Spot	BTC CBOE
IS (Hasbruck)	0.0500	0.9500	0.0612	0.9388	0.0758	0.9242
CS (Gonzalo)	0.2104	0.7896	0.2423	0.7577	0.3129	0.6871
IL (Yan)	0.1976	5.0608	0.2039	4.9032	0.1801	5.5514
ILS (Putnins)	0.0376	0.9624	0.0399	0.9601	0.0314	0.9686
BTC CME vs BTC CBOE	BTC CME	BTC CBOE	BTC CME	BTC CBOE	BTC CME	BTC CBOE
IS (Hasbruck)	0.4660	0.5340	0.4795	0.5205	0.4505	0.5495
CS (Gonzalo)	0.2904	0.7096	0.2658	0.7342	0.2560	0.7440
IL (Yan)	2.1329	0.4689	2.5440	0.3931	2.3834	0.4196
ILS (Putnins)	0.8198	0.1802	0.8662	0.1338	0.8503	0.1497

in CBOE Bitcoin futures. Further, the reversal of informational flows from Bitcoin spot through Bitcoin futures (Corbet et al., 2018a) is largely a result of a substantial increase in the number of informationally astute, institutional investors.

4. Conclusions

In examining the argument as to whether cryptocurrencies at large are best described as a speculative asset rather than that of a currency, this research presents three key results that provide evidence supporting the development of the market for Bitcoin. First, there is evidence that breakpoints across both spot and both futures markets have responded at large to substantial regulatory and fraudulent events, presenting evidence of both efficiency and consideration by traders as to the long-term reputational damage set out in such releases. Secondly, while earlier research found that information flows and price discovery were transmitted from spot to futures markets, this research verifies that this relationship has since reversed, most likely explained by the influx of institutional and sophisticated investors. Finally, a novel finding is found in the information flows transmitted from CBOE through CME Bitcoin futures, as results most likely best explained through structural differences between both products. We can clearly observe that cryptocurrency derivatives markets, while in their relative youth have portrayed evidence of stabilisation and price discovery, with results that are robust across multiple metrics and frequencies.

References

Bai, J., 1997. Estimation of a change point in multiple regression models. Rev. Econ. Stat. 79, 551–563.
Bai, J., Perron, P., 1998. Estimating and testing linear models with multiple structural changes. Econometrica 47–78.
Bohl, M.T., Salm, C.A., Schuppli, M., 2011. Price discovery and investor structure in stock index futures. J. Fut. Mark. 31, 282–306.
Corbet, S., Eraslan, V., Lucey, B.M., Sensoy, A., 2019. The effectiveness of technical trading rules in cryptocurrency markets. Finance Res. Lett. 31, 32–37.
Corbet, S., Lucey, B., Peat, M., Vigne, S., 2018. Bitcoin futures - what use are they? Econ. Lett. 172, 23–27.
Corbet, S., Lucey, B., Urquhart, A., Yarovaya, L., 2019. Cryptocurrencies as a financial asset: a systematic analysis. Int. Rev. Financ. Anal. 62, 182–199.
Corbet, S., Lucey, B., Yarovaya, L., 2018. Datestamping the Bitcoin and Ethereum bubbles. Finance Res. Lett. 26, 81–88.
Corbet, S., Meegan, A., Larkin, C., Lucey, B., Yarovaya, L., 2018. Exploring the dynamic relationships between cryptocurrencies and other financial assets. Econ. Lett. 165, 28–34.
Fry, J., 2018. Booms, busts and heavy-tails: the story of Bitcoin and cryptocurrency markets? Econ. Lett. 171, 225–229.
Gandal, N., Hamrick, J., Moore, T., Oberman, T., 2018. Price manipulation in the Bitcoin ecosystem. J. Monet. Econ. 95, 86–96.
Göktaş, P., Dişbudak, C., 2014. Modelling inflation uncertainty with structural breaks case of Turkey (1994–2013). Math. Probl. Eng. 2014.
Gonzalo, J., Granger, C., 1995. Estimation of common long-memory components in cointegrated systems. J. Bus. Econ. Stat. 13, 27–35.
Hasbrouck, J., 1995. One security, many markets: determining the contributions to price discovery. J. Finance 50, 1175–1199.

Hauptfleisch, M., Putniņš, T.J., Lucey, B., 2016. Who sets the price of gold? London or New York. J. Fut. Mark. 36, 564–586.
Katsiampa, P., 2017. Volatility estimation for Bitcoin: a comparison of GARCH models. Econ. Lett. 158, 3–6.
Katsiampa, P., Corbet, S., Lucey, B., 2019. Volatility spillover effects in leading cryptocurrencies: A BEKK-MGARCH analysis. Finance Res. Lett. 29, 68–74.
Mensi, W., Lee, Y.-J., Al-Yahyaee, K.H., Sensoy, A., Yoon, S.-M., 2019. Intraday downward/upward multifractality and long memory in Bitcoin and Ethereum markets: An asymmetric multifractal detrended fluctuation analysis. Finance Res. Lett. 31, 19–25.
Putniņš, T.J., 2013. What do price discovery metrics really measure? J. Empir. Finance 23, 68–83.
Sensoy, A., 2019. The inefficiency of Bitcoin revisited: ahigh-frequency analysis with alternative currencies. Finance Res. Lett. 28, 68–73.
Urquhart, A., 2016. The inefficiency of Bitcoin. Econ. Lett. 148, 80–82.
Urquhart, A., 2017. Price clustering in Bitcoin. Econ. Lett. 159, 145–148.
Yan, B., Zivot, E., 2010. A structural analysis of price discovery measures. J. Financ. Mark. 13, 1–19.