Bitcoin Futures - What use are they?

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Abstract

Early analysis of Bitcoin concluded that it did not meet the economic conditions to be classified as a currency. Since this analysis interest in bitcoin has increased substantially. We investigate whether the introduction of futures trading in bitcoin is able to resolve the issues that stopped bitcoin from being considered a currency. Our analysis shows that spot volatility has increased following the announcement of the futures contracts, the futures contracts are not an effective hedging instrument and that price discovery is driven by uninformed investors in the spot market. The conclusion that bitcoin is a speculative asset rather than a currency is not altered by the introduction of futures trading.

Keywords: Cryptocurrencies; Futures markets; Volatility; Speculative Assets; Currencies.

1. Introduction

An early analysis of bitcoin by Yermack [2015] concluded that it was not a currency, but rather a speculative asset. He argued that bitcoin failed to satisfy the functions of money: a medium of exchange, unit of account and store of value. The idea that bitcoin has no intrinsic value, such as Cheah and Fry [2015] supports this conclusion. A recent innovation in the bitcoin trading environment is the introduction of futures contracts by the Chicago Mercantile Exchange (CME) and Chicago Board Options Exchange (cboe) in December 2017. The high volatility of bitcoin prices was identified by Yermak as a feature which lead to bitcoin not being a useful unit of account. We examine the relationship between the futures and spot, finding that by contrast to the norm, cash leads the futures. This we surmise is related to the very high volatility of bitcoin.

In December 2017 trading in futures contracts on bitcoins commenced on the Chicago Mercantile Exchange (CME) and the Chicago Board Options Exchange (cboe). On December 1 both exchanges announced a bitcoin futures contract. The cboe contract commenced trading on December 10, each contract is for one bitcoin. Three aspects of the introduction of futures on the spot market will be explored. Firstly the impact of futures trading on spot volatility is examined. Secondly the hedging effectiveness of the futures contracts is evaluated. Finally the flow of information between the spot and futures markets is documented.

2. Data

The CBOE contract commenced trading on December 10, each contract is for 1 bitcoin1. Both it and the later CME contract contracts are cash settled in USD. Shown in Table 1 are stylized facts of these two contracts. Using data sampled at a one minute frequency from the CBOE futures contract, sourced from Thomson Reuters Tick History, and bitcoin price data from coinmarketcap.com[1], we explore the impact of the introduction of risk management tools on the pricing and risk characteristics of the spot bitcoin market. From the 1-minute transaction prices we calculate the log return for each period, which is presented in Figure 1.

Insert Table 1 & Figure 1 about here

The characteristics of bitcoin data covering the period from 26 September 2017 to 22 February 2018 can be found in Table 2. Statistics for the full period and for sub-samples before and after the introduction of futures trading are presented.

Insert Table 2 about here

Clearly there has been a change in the distributional characteristics of bitcoin returns since futures. The mean changed sign and the standard deviation doubled. This change in volatility is evident in the time series plot of the returns.

3. Analysis

The impact of the introduction of futures trading on volatility in the underlying spot market has been investigated for stocks, foreign exchange, interest rates and commodities. The empirical evidence is mixed. Gulen and Mayhew [2000] found a noticeable increase in volatility in the U.S. and Japan but in the remaining 23 markets there was a negligible effect or the volatility fell. A recent study of the introduction of futures on European real estate

[1]A website which collects Bitcoin data from multiple exchanges and combines it to form a weighted average.

indices by Lee et al. [2014] found that the volatility of the indices *fell* after the introduction of the futures contracts.

We apply tests from the process control literature . These are fully described in Ross et al. [2011] and Ross et al. [2015] to which the interested reader is directed. The R statistical package *cpm*, from Ross et al. [2015] was used for all estimation

Two nonparametric statistics are computed, the *Mood* statistic for change in volatility (scale) and a *Lepage-(type)* statistic which tests for a change in location and scale, the results of which are presented in Figure 2.

Insert Figure 2 about here

Both the Mood and Lepage statistics indicate a significant change in the distribution, driven by the increase in volatility. The date of the change is 29 November 2017, two days before the official announcement of the commencement dates for futures trading. As returns for financial assets have often been found to be non i.i.d. the analysis was run on both the raw returns and residuals from a ARMA(1,1)-GARCH (1,1). A significant change in the distribution, associated with the increase in series volatility was detected at 29 November 2017 in each case.

We now measure the extent of risk reduction that can be obtained by forming hedge portfolios. It is possible that an appropriately constructed hedge portfolio can be used to manage the volatility of bitcoin prices. Hedging literature such as Figlewski [1984]; Kroner and Sultan [1993]; Park and Switzer [1995]; Choudhry [2003], concludes that hedge ratios selected by OLS generally work best when evaluated in sample. We will analyse naÃŕve and OLS based hedging strategies. The effectiveness of the hedge can be measured by the percentage reduction volatility that results from holding the hedge portfolio. We will also compute Hedge Effectiveness using Semi-variance, which measures the variability of returns below the mean, addressing a shortcoming of the variance and providing a more intuitive measure of risk for hedging focusing on downside risk.

Two hedging approaches are evaluated. The first is the naive hedge which is a portfolio with one short futures position for every bitcoin position. The second approach is the ordinary least squares (OLS) hedge. A simple OLS regression of the form $r_{spot} = \alpha + \beta_{future}$ is run. The estimated β is used as the hedge ratio. This approach to hedging is implemented using a rolling regression framework. In this work β is estimated each day then used to compute the hedge portfolio return for the next day. The return series for the hedge is the concatenation of each days hedge portfolio return. Table 3 contains the results of the evaluation of hedge effectiveness.

Insert Table 3 about here

The first and most striking result is that hedging increases risk, as indicated by the negative sign of the effectiveness and risk reduction results. While the rolling OLS hedge is more effective than the naive hedge, as would be expected, it also increases the pricing risk inherent in holding physical bitcoin. Using semi-variance in the computation of hedge effectiveness shows an improvement in effectiveness compared to the use of the variance. However both the hedging strategies are shown to be risk increasing under all evaluation methods.

It is generally accepted that futures contracts lead their respective underlying assets in price discovery, Bohl et al. [2011]; Rosenberg and Traub [2009]; Cabrera et al. [2009]; Hauptfleisch et al. [2016]. These results highlight the importance of market structure and instrument type. The findings of these studies indicate that the centralisation and relative transparency of futures markets contribute to their large role in price discovery. It is also likely that low transaction costs, inbuilt leverage, ease of shorting and the ability to avoid holding the underlying physical asset make futures contracts an attractive alternative for traders in a wide range of assets. Bohl et al. [2011] argue that the emergence of futures markets generally coincides with the rise of instructional trading. The trades of sophisticated institutional investors contributes to price discovery being focused in futures markets.

There are 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). 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):

$$\Delta_{p1,t} = \alpha_1(p_{1,t-1} - p_{2,t-1}) + \sum_{i=1}^{200} \gamma_i \Delta p_{1,t-i} + \sum_{j=1}^{200} \delta_j \Delta p_{2,t-j} + \varepsilon_{1,t} \tag{1}$$

$$\Delta_{p2,t} = \alpha_2(p_{1,t-1} - p_{2,t-1}) + \sum_{k=1}^{200} \varphi_k \Delta p_{1,t-k} + \sum_{m=1}^{200} \phi_m \Delta p_{2,t-m} + \varepsilon_{2,t} \tag{2}$$

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 to the vector of error correction coefficients, therefore:

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

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

$$ILS_1 = \frac{\left|\frac{IS_1}{IS_2}\frac{CS_2}{CS_1}\right|}{\left|\frac{IS_1}{IS_2}\frac{CS_2}{CS_1}\right| + \left|\frac{IS_2}{IS_1}\frac{CS_1}{CS_2}\right|} \text{ and } ILS_2 = \frac{\left|\frac{IS_2}{IS_1}\frac{CS_1}{CS_2}\right|}{\left|\frac{IS_1}{IS_2}\frac{CS_2}{CS_1}\right| + \left|\frac{IS_2}{IS_1}\frac{CS_1}{CS_2}\right|} \tag{7}$$

We estimate all three price discovery metrics, noting that they measure different aspects of price discovery.

Insert Table 4 about here

The results in Table 4 show that the spot market leads in price discovery according to all the metrics computed. This result is contrary to what has been found in a range of other asset classes, where futures markets lead. Looking at the Information Leadership Share 97% of the information affecting bitcoin prices is reflected in the spot market, the remaining 3% is reflected in the futures market. The concentration of price discovery in the spot market may be a function of the novelty of the new futures contracts, they have been trading for 3 months. It may also be the case that the type of investor attracted to bitcoin because of its anonymity may not be inclined to begin trading on a registered and regulated futures market, where personal details have to be given before trading is permitted, these

[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, $\Omega = MM'$

investors would in general be classified as uninformed. Because of various restrictions on bitcoin there is an absence of a large cohort of institutional investors who have positions in physical bitcoin. The results presented support the argument put forward by Bohl et al. that the dominance of unsophisticated individual investors in the futures market impedes its contribution to price discovery.

4. Conclusions

The economic attributes of a currency are; it is a medium of exchange, a store of value and a unit of account. Yermack [2015] asserted that bitcoin was not a currency as it 'performs poorly as a unit of account and as a store of value'. The high volatility of bitcoin prices and the range of prices quoted on various bitcoin exchanges were seen to damage bitcoin's usefulness as a unit of account. If the introduction of trading in bitcoin futures resulted in a reduction in the variance of bitcoin prices, or facilitated hedging strategies that could mitigate pricing risk in the spot market it is possible that bitcoin could act as a unit of account, moving it closer to being a currency. The analysis conducted shows that volatility increased around the announcement of trading in bitcoin futures. In the period covered by this study hedge portfolios constructed with the futures cannot mitigate the risk inherent in the underlying spot market, both of the hedging strategies considered resulted in an increase in volatility. The price discovery analysis indicated that price discovery is focused on the spot market, which is in keeping with the argument that the traders in the futures market are uninformed noise traders. Together these results support Yermak's conclusion that bitcoin should be seen as a speculative asset rather than a currency.

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Figure 1: Price and returns time series over the full sample period

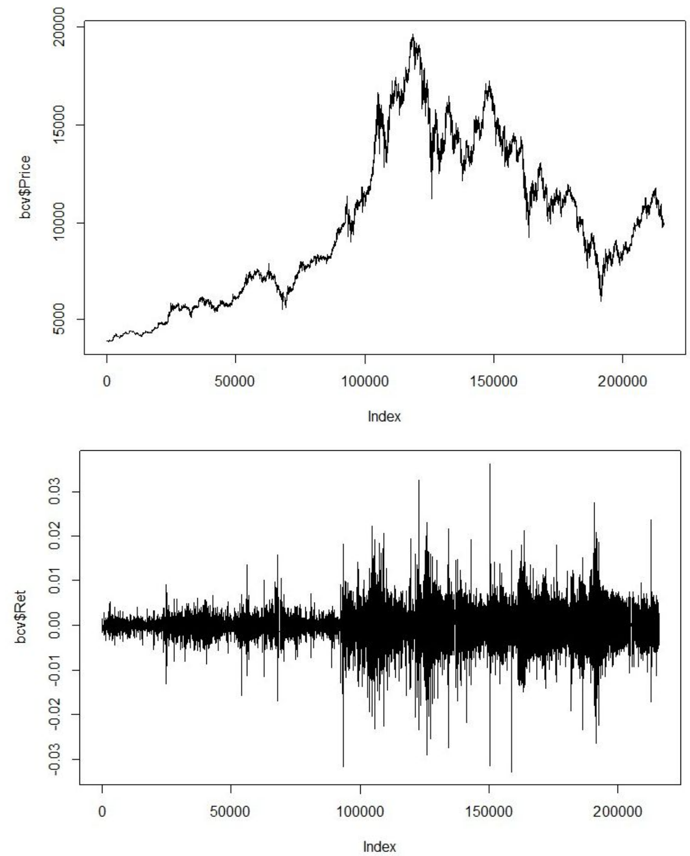
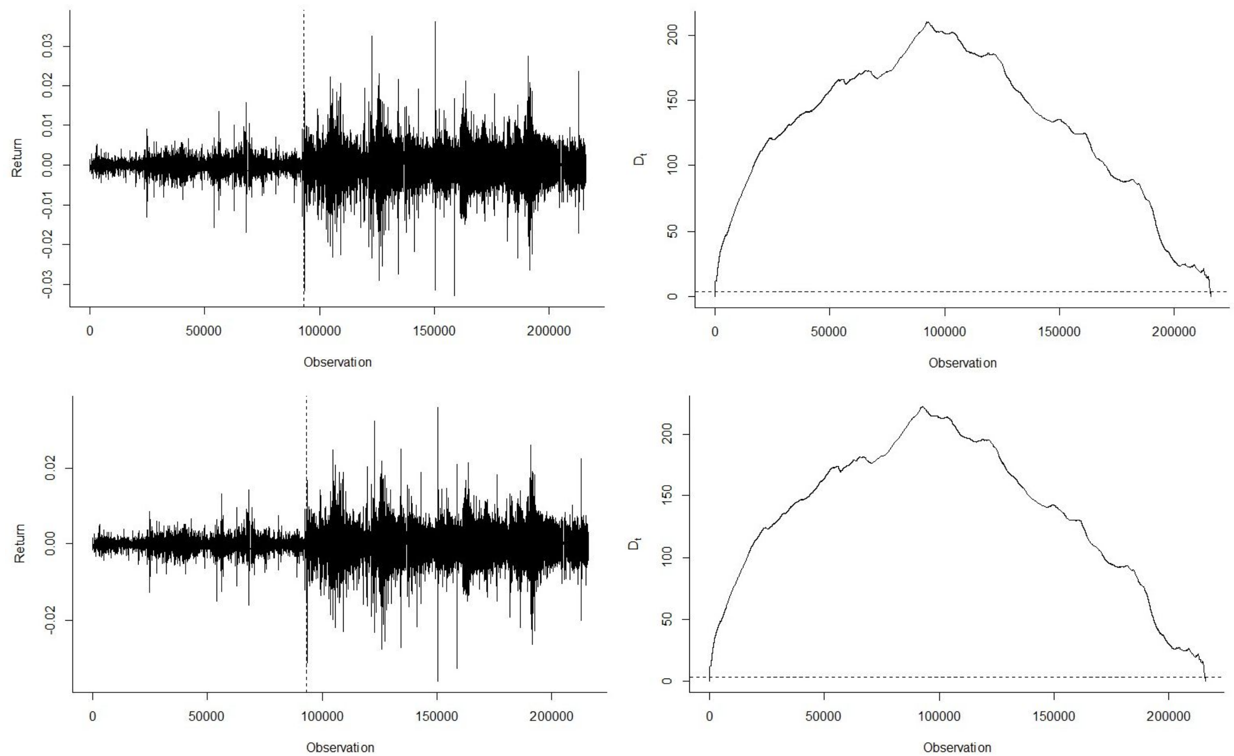


Figure 2: Change Point Detection



Note: The above figure presents the Raw Returns Mood Statistics (Top Panel) and GARCH(1,1) Residuals Mood Statistic (Bottom Panel) respectively. These two nonparametric statistics represent the Mood statistic for change in volatility (scale) and a Lepage type statistic which tests for a change in location and scale respectively. The implementation of these statistics for change point detection the cpm package was used to establish the existence and location of a change point in the bitcoin price series. Both the Mood and Lepage statistics indicate there is a significant change in the distribution, driven by the increase in volatility. The date of the change is 29 November 2017, two days before the official announcement of the commencement dates for futures trading.

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
Minimum Price Fluctuation	10.00 points USD/XBT (equal to $10.00 per contract)	$5.00 per bitcoin = $25.00 per contract
Position Limits	A person: (i) may not own or control more than 5,000 contracts net long or net short in all XBT futures contract expirations combined and (ii) may not own or control more than 1,000 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.	1,000 contracts with a position accountability level of 5,000 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

Note:

Table 2: Descriptive Statistics for Bitcoin Prices and Returns

Panel A - *Full Sample*	Price	Return
Mean	9,862.048	4.26E-06
Standard Error	8.579189	4.33E-06
Median	9,291.53	1.21E-06
Mode	15,000	0.000000
Standard Deviation	3,984.44	0.002009
Sample Variance	15,875,760	4.04E-06
Kurtosis	-0.89573	11.46425
Skewness	0.39184	-0.08776
Range	15,800.5	0.069144
Minimum	3,865.23	-0.03291
Maximum	19,665.73	0.036236
Count	215,696	215,696

Panel B - *Pre Futures Introduction*	Price	Return
Mean	7,812.788	1.3E-05
Standard Error	10.39188	3.96E-06
Median	6,671.42	1.1E-05
Mode	16,500	0.000000
Standard Deviation	3,559.035	0.001357
Sample Variance	12,666,728	1.84E-06
Kurtosis	0.845098	26.04
Skewness	1.322531	-0.43248
Range	14,152.89	0.053846
Minimum	3,865.23	-0.03166
Maximum	18,018.12	0.022191
Count	117,294	117,294

Panel C - *Post Futures Introduction*	Price	Returns
Mean	12304.74	-6.1E-06
Standard Error	9.418187	8.22E-06
Median	11,683.09	0.000000
Mode	15,000	0.000000
Standard Deviation	2,954.4	0.00258
Sample Variance	8,728,479	6.66E-06
Kurtosis	-0.58609	6.020228
Skewness	0.302747	-0.00718
Range	13,741.01	0.069144
Minimum	5,924.72	-0.03291
Maximum	19,665.73	0.036236
Count	98,402	9,8402

Table 3: Hedge Effectiveness

Naive Hedge	
Risk Reduction	-334.59
Hedge Effectiveness	-3.3459
Hedge Effectiveness (semivarance)	-1.20851

Rolling OLS Hedge	
Risk Reduction	-60.7627
Hedge Effectiveness	-0.60763
Hedge Effectiveness (semivarance)	-0.38919

Table 4: Price Discovery Results

Information Share (Hasbruck)	*Lower Bound*	*Upper Bound*	*Average*
Futures	0.115535	0.183738	0.149637
Bitcoin	0.816261	0.884465	0.850363

Component Share (Gonzalo)	*Average*
Futures	0.177028
Bitcoin	0.822971

Information Leadership (Yan)	*Average*
Futures	0.025636
Bitcoin	0.827931

Information Leadership Share (Putnins)	*Average*
Futures	0.030034
Bitcoin	0.969965