Bitcoin futures: An effective tool for hedging cryptocurrencies

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Abstract: In December 2017, the CBOE and CME launched bitcoin futures, arguing that, similar to other futures, these contracts would provide more price transparency, price discovery, and a risk management tool for bitcoin. Using daily data from several sources, this paper investigates the hedging properties of CBOE Bitcoin futures during these initial months of trading. The results point out that bitcoin futures are effective hedging instruments not only for bitcoin, but also for other cryptocurrencies. Bitcoin futures can even cope with bitcoin tail risk, however they may leverage the existence of extreme losses for other currencies.

JEL classification: G12, G14, G15, G23

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1. Introduction

In December 2017, at the peak of an exponential bull price rally of bitcoin and other cryptocurrencies, the Chicago Board Options Exchange (CBOE) and the Chicago Mercantile Exchange (CME) begun trading bitcoin futures. The exchanges pointed out that this meant the creation of an organized and transparent market for trading a bitcoin product, and, as such, bitcoin futures would accelerate the price discovery process and provide an efficient tool for hedging price risk. In fact, these economic benefits, usually attributed to other futures markets, gain special appeal in the case of bitcoin.

This paper aims to assess the hedging effectiveness of bitcoin futures, not only in relation to bitcoin, but also in relation to other cryptocurrencies. Corbet et al. (2018a) have already tackled this issue for bitcoin by analysing the daily hedging effectiveness of OLS hedge ratios estimated using the previous day 1-minute returns. The authors obtain a negative value for the traditional hedging effectiveness measure (i.e., the reduction in the variance of the unhedged portfolio achieved by including a short position in the futures contract), meaning that hedging with these futures not only does not reduce significantly the risk but instead increases it, which is at odds with the literature on futures hedging.

Our results show that, in the initial trading months, for the period from 11-Dec-2017 to 05-Feb-2019, CBOE bitcoin futures have been an effective instrument for daily hedging not only bitcoin, but also other cryptocurrencies, such as ethereum, litecoin and ripple. These futures contracts can even cope with bitcoin tail risk, however they may leverage the existence of extreme losses for the other currencies.

2. Literature review

Bitcoin and other cryptocurrencies are traded worldwide around the clock (24/7) in multiple online exchanges, and there is clear evidence that bitcoin prices are not arbitraged away, even between those exchanges with the higher market shares (see, for instance, Pieters and Vivanco, 2017, and Makarov and Schoar, 2018), and consequently transmission of information between exchanges can last for several hours or even days (Sebastião et al., 2017, and Matkovskyy, 2019). On the other hand, the volatility of bitcoin has been quite high, sustaining the view that it is a new kind of tradable speculative asset, which, at most, can work as imperfect substitute for traditional currencies (Dyhrberg, 2016). The bitcoin volatility has been addressed by several authors, such as Bariviera (2017), Blau (2017), Katsiampa (2017), Gkillas and Katsiampa (2018), among others.

Given its novelty, research on bitcoin futures is still scarce. An initial line of research was to assess the impact of futures trading on the price, volatility and efficiency of bitcoin. At the time of launching of these futures contracts, the bitcoin price initiated a steep descending path and naturally the two events were perceived as associated. Hale et al. (2018) argue that bitcoin futures allowed pessimists to enter the market, which contributed to the reversal of the bitcoin price dynamics. This idea is also shared by Baur and Dimpfl (2019), who argue that with bitcoin futures investors can bet against bitcoin in a regulated framework with margin requirements far below the ones required previously. Corbet et al. (2018a) use 1-minute price data to show that bitcoin volatility has increased after the introduction of futures contracts. On the other hand, using daily data, Köchling et al. (2018) conclude that the launching of bitcoin futures has in fact increased the informational efficiency of bitcoin, but there is no visible effect on other cryptocurrencies, such as ethereum, litecoin, ripple and bitcoin cash. The authors argue that the improved bitcoin efficiency is due to the easing of institutional investors access to the bitcoin market provided by these futures contracts.

Most of the research has been directed to the study of the relative price discovery process taking place in the spot and futures markets using long-run price discovery metrics derived from VECM models, such as Hasbrouck information shares and Gonzalo-Granger common factor weights. Baur and Dimpfl (2019), using 5-minute trade prices of CME and CBOE futures and bitcoin at Bitstamp for the period since the introduction of these futures until 18-Oct-2018, conclude that price discovery takes place mostly in the spot market. The authors suggest that this is probably due to the superior trading volume of bitcoin worldwide, and to futures trading being interrupted daily and during weekends while bitcoin is traded 24/7. Using 1-minute data, from 26-Sep-2017 to the 22-Feb-2018, on the bitcoin price index and CBOE futures sourced from Thomson Reuters, Corbet et al. (2018a) claim that price discovery is driven by uninformed investors in the spot markets, as the information transmission occurs mainly from the spot to the futures market (from the several metrics used by the authors, the most that futures market achieves is a 17.7% share). Kapar and Olmo (2019) also analyse this topic but they reach a different conclusion. Using daily data on the Coindesk Bitcoin USD Price Index and the CME futures contracts from 12-Dec-2017 to 16-May-2018, they point out that deviations from the long-run relationship have predictive ability on the bitcoin returns but not on the futures returns and consequently most of the price discovery occurs in the futures market (the Hasbrouck Information Share of the futures market achieves a value of 89%).

As stated earlier, we aim to study the hedging effectiveness on bitcoin and other cryptocurrencies. So, it is noteworthy to mention that, although at the first glance one may think that price dynamics of bitcoin and other cryptocurrencies are quite similar, they may also have different features, especially in a high frequency framework. Hence results for bitcoin cannot be readily translated to other cryptocurrencies. For instance, Bariviera et al. (2018) applied the complexity-entropy causality plane to the 5-minute data of 12 cryptocurrencies and conclude that most of them share the same dynamics with bitcoin, but ethereum and ethereum classic exhibit a more persistent stochastic dynamics, while dash and NEM have a behaviour closer to a random walk.

Most notably, the hedging effectiveness of bitcoin futures on other cryptocurrencies depends on the correlations between them and bitcoin. Corbet et al. (2018b) and show that bitcoin, litecoin and ripple are highly connected to each other at different frequencies and that these linkages are time-varying. Aslanidis et al. (2019) apply a generalized DCC class model to bitcoin, dash, monero, and ripple and reach similar results, namely that correlations among cryptocurrencies are positive, albeit varying across time. Cahn et al. (2019) show that structural breaks are present in the 7 cryptocurrencies under study, the shifts spread from smaller cryptocurrencies (in market capitalization) to larger ones, and that the conditional quasi-correlations obtained from a DCC-MGARCH model are significantly positive and large (more than 0.4, with the highest one being 0.75 for the pair bitcoin/litecoin). All these results, obtained from daily series, highlight that if bitcoin futures are effective in hedging daily bitcoin price risk, then they may also produce risk reduction benefits, although at different degrees, for other cryptocurrencies.

3. Data and preliminary analysis

The CBOE Bitcoin (USD) Futures Contract (acronym XBT) has a multiplier of 1 bitcoin, and the tick size is 5 USD. These are monthly contracts, cash-settled according to the daily 4 p.m. auction USD price at the Gemini Exchange, in the third Wednesday of each calendar month. XBT futures are available for trading almost around the clock during business days. The trading session begins with a period of extended trading hours from 5 p.m. of the previous day until 8:30 a.m.. At that time the regular market begins, ending at 3:15 p.m., when the settlement price is computed. Then follows a pause of fifteen minutes, and, finally, an additional extended market is available from 3:30 p.m. until 4:00 p.m. Expiring XBT futures end trading at 2:45 p.m., i.e. 15 minutes before the auction at the Gemini Exchange.

Daily data on bitcoin futures were obtained from the CBOE site (http://www.cboe.com/). Since 11-Dec-2017, beginning with the XBT Jan-2018 contract, until the present time (05-02-2019), were issued 17 monthly contracts, from which 13 have reached their delivery dates. The time series of close prices were constructed rolling over the nearby contract at the last trading day, covering a total of 290 business days.

The spot data was collected from three sources. Daily 4 p.m. auction prices were gathered from the Gemini Exchange site (https://gemini.com/). Since the launch of XBT futures there were only 6 business days without these prices. These gaps were firstly filled using the price cleared at the 6 a.m. auction at Gemini, and, if this price was not available, linear interpolation was used.

Daily prices, recorded at 00:00:00 UTC (next day), of bitcoin (these series are denoted hereafter as CMC), ethereum (ETH) litecoin (LTC) and ripple (XRP) in USD, were obtained from the CoinMarketCap site (https://coinmarketcap.com/). These are the most important cryptocurrencies in terms of market capitalization, media coverage and data availability. Notice that these are not trading prices but instead weighted average prices considering the previous 24h market shares of online cryptocurrency exchanges. These daily observations lead the XBT close prices by 2h (when Chicago is in the Central Standard Time - CST) or 3h (when the Central Daylight Time - CDT- is in place), except on delivery days, when the time lead expands for more 1h15min.

In order to provide a more precise analysis on the hedging properties of XBT futures, tick data were collected from Bitstamp. This online exchange has played, since the bankruptcy of MtGox, an important role in transmitting information on the USD/bitcoin hourly prices (Sebastião et al., 2017), has a relevant position in terms of trading volume USD/bitcoin (Hileman and Rauchs, 2017) and is one of the exchanges from which CME computes the Bitcoin Reference Rate (BRR), the settlement price of its bitcoin futures. The exchange trade data is publicly available at the Bitcoincharts site (https://bitcoincharts.com/). Bitstamp prices were daily sampled considering the best synchronization with the futures close prices, not forgetting the time lag (UTC-6:00 in standard time and UTC-5:00 in daylight saving time) and the different closing time in the futures expiration days.

Table 1 shows the descriptive statistics of the daily logarithmic returns of the nearby XBT futures, bitcoin (considering the three data sources), and the other three cryptocurrencies.

Table 1
Descriptive statistics of the logarithmic returns

	Futures	Bitcoin			Other cryptocurrencies		
	XBT	Gemini	Bitstamp	CMC	ETH	LTC	XRP

Mean (%)	-0.595**	-0.560*	-0.555*	-0.549*	-0.542	-0.634	0.060
Median (%)	-0.279	-0.248	-0.185	-0.007	-0.353	-0.834	-0.560
Minimum (%)	-22.12	-22.28	-24.60	-23.87	-27.16	-22.93	-54.74
Maximum (%)	14.04	15.98	14.90	15.18	24.74	38.93	60.69
Std. Dev. (%)	4.945	4.847	4.909	4.920	6.848	6.584	9.770
Skewness	-0.452	-0.457	-0.671	-0.606	-0.002	0.987	1.186
Exc. kurtosis	1.906	2.449	2.886	2.631	1.892	5.848	10.87
ρ(1)	-0.016	-0.010	-0.043	-0.064	-0.013	-0.038	0.076
Ccorr(XBT,Crypto)	-	0.961***	0.981***	0.903***	0.649***	0.678***	0.445***

Notes: ρ(1) is the autocorrelation of order 1 and Ccorr(XBT,Crypto) is the contemporaneous cross-correlation between the returns of the nearby futures contract and the returns of each cryptocurrency. Significance of the mean values was assessed using the Newey-West robust standard errors, with a bandwidth 3 (Bartlett kernel). Significance at the 1%, 5% and 10% levels are denoted by *, **, ***, respectively.

The daily mean returns are negative, except for XRP, and especially the mean return of the futures contract, -0.6%, which is significant at the 5% level. The median values are generally above the mean, except for LTC and most notably for XRP. The returns ranges are impressive, especially for XRP, implying that in just one day an investor with a long position in this cryptocurrency would gain exp(0.6069) - 1 = 83.5%, but she would lose exp(-0.5474) - 1 = -42.2% of her investment in just another day. The bitcoin volatility is about 8 to 9 times the magnitude of expected returns. This factor increases to an impressive value of 163 for XRP. The bitcoin series are negatively skewed and show mild excess kurtosis. None of the series show significant first order autocorrelation, but all cryptocurrencies are highly contemporaneously correlated with the futures contract, with these cross-correlations being higher than 0.9 for bitcoin, near 0.7 for ETH and LTC, but only 0.5 for XRP. In sum, for the period from 11-Dec-2017 to 05-Feb-2019, the series share several statistical features, although XRP seems quite diverse from the other series.

4. Hedging with CBOE bitcoin futures

This section presents the hedging results for daily horizons, for bitcoin, considering the three data sources (Table 2) and for ethereum, litecoin and ripple (Table 3). Here, the assumption is that if bitcoin is highly correlated with other cryptocurrencies, then bitcoin futures may provide an effective tool to manage the price risk of these digital currencies (cross-hedge).[1]

Table 2
Hedging bitcoin with CBOE bitcoin futures

Panel A – Gemini	Spot	Naïve	OLS	DCC-GARCH
Mean hedge ratio			0.920***	0.928***
Hedge ratio range			[0.819, 1.036]	[0.751, 1.232]
Mean	-0.534	0.005**	-0.037**	0.016**
Minimum	-15.23	-4.645	-5.172	-4.915
Maximum	14.76	5.172	4.694	5.653

[1] Besides the moving window OLS and the standard DCC-GARCH methodologies, we also analysed the hedging results for robust regression using iteratively reweighted least squares with the bisquare weighting function, Asymmetric DCC-GARCH and DCC-GARCH with Laplace errors. We have considered for each model both fixed length and expanding windows. The results are most of the times marginally worse, and due to space reasons are not reported here, but they can be obtained from the authors on request.

Variance	0.166	0.019***	0.018***	0.019***
		(88.69)	(89.19)	(88.69)
Semivariance	0.091	0.009***	0.009***	0.009***
		(90.12)	(90.17)	(90.27)
CVaR at 5%	3.589	1.087***	0.967**	0.923**
		(69.70)	(73.05)	(74.27)
Panel B – Bitstamp	Spot	Naïve	OLS	DCC-GARCH
Mean hedge ratio			0.976***	0.975**
Hedge ratio range			[0.946, 1.004]	[0.886, 1.150]
Mean	-0.537	0.002**	-0.009**	0.018**
Minimum	-15.15	-3.306	-3.521	-3.693
Maximum	11.60	4.735	4.612	5.309
Variance	0.163	0.005***	0.005***	0.005***
		(97.10)	(97.19)	(96.82)
Semivariance	0.091	0.002***	0.002***	0.002***
		(97.67)	(97.65)	(97.45)
CVaR at 5%	3.420	0.871**	0.887**	0.890**
		(74.54)	(74.07)	(73.99)
Panel C – CMC	Spot	Naïve	OLS	DCC-GARCH
Mean hedge ratio			0.872***	0.847***
Hedge ratio range			[0.793, 0.944]	[0.639, 1.200]
Mean	-0.526	0.013**	-0.053*	-0.033*
Minimum	-14.00	-5.633	-4.802	-4.676
Maximum	10.82	7.377	7.111	7.061
Variance	0.147	0.025***	0.022***	0.024***
		(83.13)	(85.17)	(83.45)
Semivariance	0.081	0.012***	0.010***	0.011***
		(85.46)	(87.58)	(85.89)
CVaR at 5%	2.927	1.133	0.681**	0.768**
		(61.28)	(76.73)	(73.76)

Notes: All values are in percentage, except the mean hedge ratio and the hedge ratio range. In parentheses are the hedging effectiveness measures, i.e. the reduction in the corresponding risk statistic of the unhedged portfolio achieved by taking a short position in the futures market (Cotter and Hanly, 2006). The semivariance corresponds to the second order lower partial moment with a target equal to the mean return. The CVaR at 5% measures the mean loss conditional upon the fact that the VaR at the 5% level has been exceeded. The naïve means "the equal and opposite hedge", i.e. a constant unity hedge ratio. OLS hedge is generated by applying the coefficient of the linear regression of the spot returns on the futures returns to the next day of a moving window of fixed length of 100 obs.. The DCC-GARCH methodology applies the model proposed by Engle (2002). The resulting hedge ratios are estimated using an expanding window beginning with 100 obs., and are applied recursively to the next day. The significance levels are determined using 10000 bootstrap samples, created with the stationary block procedure proposed by Politis and Romano (1994), with an optimal block size chosen according to Politis and White (2004). For the mean hedge ratio, the null hypothesis is the equality to unity (naïve hedge), whilst for the variance, semivariance and CVaR, the null hypothesis is the risk statistic being equal to the corresponding statistic of the spot (unhedged portfolio). Significance at the 1%, 5% and 10% levels are denoted by *, **, ***, respectively.

The naïve hedging approach reduces the variance, semivariance and CVaR5% by at least 83%, 85% and 61%, respectively. The OLS and DCC-GARCH hedge ratios are on average significantly lower than unity, but these ratios only produce marginal improvements on the risk reduction achieved by the naïve hedge (the differences on the risk and effectiveness metrics have at most a magnitude of 10^{-4}). Two overall results deserve special attention: First, it seems that the best results are achieved for Bitstamp, i.e. the best results are obtained for real trade data from a continuous market and not for the auction price at the Gemini Exchange nor for the volume weighted average prices (VWAP) of CoinMarketCap, and, second, there is some evidence that bitcoin futures can deal with bitcoin tail risk.

Table 3
Hedging ETH, LTC and XRP with CBOE bitcoin futures

Panel A – ETH	Spot	Naïve	OLS	DCC-GARCH
Mean hedge ratio			1.010	1.133
Hedge ratio range			[0.726, 1.328]	[0.543, 2.094]
Mean	-1.031	-0.492*	-0.511*	-0.291**
Minimum	-20.69	-16.44	-16.50	-16.73
Maximum	24.74	19.06	18.34	18.85
Variance	0.373	0.169***	0.164***	0.177***
		(54.82)	(55.97)	(52.61)
Semivariance	0.186	0.081***	0.080***	0.086***
		(56.31)	(56.85)	(53.81)
CVaR at 5%	2.748	3.421	3.589	3.901
		(-24.48)	(-30.59)	(-41.96)
Panel B – LTC	Spot	Naïve	OLS	DCC-GARCH
Mean hedge ratio			0.962	0.955
Hedge ratio range			[0.773, 1.229]	[0.598, 1.646]
Mean	-0.831	-0.293*	-0.337*	-0.249*
Minimum	-14.74	-12.48	-12.50	-12.67
Maximum	22.13	12.18	11.68	13.63
Variance	0.297	0.110***	0.107***	0.118***
		(62.97)	(63.83)	(60.26)
Semivariance	0.138	0.051***	0.051***	0.054***
		(62.71)	(63.21)	(61.16)
CVaR at 5%	3.440	2.235	2.420	2.175
		(35.05)	(29.65)	(36.79)
Panel C – XRP	Spot	Naïve	OLS	DCC-GARCH
Mean hedge ratio			0.921***	0.967
Hedge ratio range			[0.743, 1.227]	[0.273, 2.028]
Mean	-0.542	-0.003*	-0.063*	-0.118*
Minimum	-18.80	-15.44	-15.43	-15.43
Maximum	32.20	33.38	33.16	33.31
Variance	0.412	0.279***	0.274***	0.297***
		(32.18)	(33.49)	(27.97)
Semivariance	0.174	0.096***	0.095***	0.102***
		(44.54)	(45.02)	(41.06)
CVaR at 5%	3.073	4.102	4.209	3.707
		(-33.48)	(-36.94)	(-20.62)

From Table 3 one can see that bitcoin futures are also effective in reducing the price risk of ethereum, litecoin and ripple, as the variances and semivariances of the hedged portfolios are always significantly lower than the variance of the spot returns (the variance and semivariance reductions range from 28% and 41.1% for XRP DCC-GARCH hedging to 63.8% and 63.2% for Litecoin OLS hedging, respectively). The mean hedge ratios are not significantly different from unity (with the exception of OLS ratio for XRP, at the 1% significance level), and show high variability, especially for XRP, where the DCC-GARCH ratios range between 0.27 and 2.03. Bitcoin futures are not able to hedge the extreme negative returns of these cryptocurrencies, and, in fact, the short positions in bitcoin futures carried out daily for hedging purposes, increased the expected shortfall at the 5% level for ethereum and ripple.

5. Conclusions

Undoubtedly, CBOE bitcoin futures are an effective hedging tool for bitcoin, at least for a daily horizon. This claim stands independently of the source used to collect the bitcoin price data and is robust to the methodology used to estimate the hedge ratios. Arguably, hedging with bitcoin futures can even mitigate significantly the impact of extreme losses in the bitcoin spot market.

The best hedging results are obtained for Bitstamp, a continuous online market for cryptocurrencies. Possible explanations may be drawn upon the time lags between the futures prices and the daily Gemini and CoinMarketCap prices, the lower trading volume at Gemini and the existence of stale prices in the VWAP computed by CoinMarketCap.

Bitcoin futures are highly correlated with other cryptocurrencies, such as ethereum, litecoin and ripple, hence these futures contracts are in fact useful for cross-hedging cryptocurrencies price risk. However, there is some evidence that the positions in the futures market may increase the tail risk.

During this period of significant daily losses, a collateral effect of hedging cryptocurrencies with bitcoin futures has been the positive effect in the mean return. Hence, other hedging effectiveness measures that besides risk also take into account the mean return, such as the difference in certainty equivalents of Hsin et al. (1994), would even produce a better image on the hedging effectiveness of bitcoin futures.

On the other hand, the liquidity of bitcoin futures has been relatively low. During the sample period, the daily trading volume of the nearby CBOE bitcoin futures contracts was only 3881 bitcoins and the daily price range (i.e. the difference between the daily high and low prices) was on average \$590, which meant approximately 7% of the corresponding daily close prices. Our results do not take into account liquidity constraints or implicit trading costs, however given the low liquidity of bitcoin futures these may be important issues for the potential hedger (see, for instance, Pennings and Meulenberg, 1997).

Our results are quite different from those of Corbet et al. (2018a), which are obtained from 1-minute data. Arguably, at this time frequency, given the low liquidity of the futures market, price dynamics may be mainly driven by microstructural noise, such as bid-ask bounce and temporary order imbalances. Those effects tend to dissipate away at lower time frequencies, hence using daily data to estimate daily hedge positions gives a better idea of the usefulness of bitcoin futures for hedging purposes.

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