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The Introduction of Bitcoin Futures: An Examination of Volatility and Potential Spillover Effects

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Abstract

Theory in Stein (1987) suggests that introducing derivative contracts, such as futures, can destabilize underlying asset prices if the contracts attract enough speculative traders. This paper examines how the introduction of Bitcoin futures influences the underlying Bitcoin market. Consistent with Stein (1987), we find that that Bitcoin's volatility increases significantly during the post-introduction period. Perhaps more importantly, however, we observe significant spillover effects into related markets. For instance, in other cryptocurrencies, the increase in volatility in these markets is greater than the post-introduction increase in Bitcoin.

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1. Introduction

Derivative contracts play an important role in completing markets (see Ross, 1976, and Nachman, 1988). Complete contingent-claims markets are important because they allow for optimal allocations of risk-bearing as described in Arrow (1964) and Debreu (1959). However, the effect of introducing derivative contracts on the stability of the underlying asset has been debated in the theoretical literature. Danthine (1978) first argued that the presence of derivative contracts makes the costs associated with arbitrage less costly. Stated differently, derivatives can lead to more arbitrage and to subsequently less mispricing and more informational efficiency, thus stabilizing asset prices (Friedman, 1953, and Ross, 1976). On the other hand, Stein (1987) suggests that introducing derivatives in markets may increase speculative trading in a particular asset. The presence of more speculation may inhibit the ability of informed traders to stabilize prices. Therefore, introducing derivatives may lead to price destabilization. Hart and Kreps (1986) find similar results in a general-equilibrium framework.

Empirical tests examining this debate seem to suggest that asset volatility decreases in response to derivative introductions. For instance, Skinner (1989) and Conrad (1989) find that stock return volatility decreases after corresponding options start trading. Edwards (1988) also shows that the introduction of futures trading also decreases the volatility of the underlying. Other studies (Bansal *et al.* 1989, and Damadoran and Lim, 1991, and Gjerde and Saettem, 1995) provide similar results.[1] While much of the literature has examined the impact of derivative introductions on equity markets, we revisit the Danthine (1978) – Stein (1987) debate by examining the recent introduction of futures contracts on the cryptocurrency Bitcoin.

The motivation for our tests is based on the idea that the cryptocurrency market, and, in particular, Bitcoin, has been dominated by speculative trading. For instance, Bouoiyour, Selmi, and Tiwari (2015) conduct a number of time-series tests and determine that at the short, medium, and long-term frequencies, speculative trading is abnormally high in Bitcoin. In addition, Hale *et al.* (2018) decomposes demand into transactional demand and speculative demand and finds the latter to be driving demand for the currency.[2] Given that the effect of derivative introductions on asset price volatility depends, in part, on speculation, the speculative nature of the cryptocurrency market makes our tests more compelling.

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[1] We note, however, that when Bollen (1998) compares the post-introduction increase in volatility in the underlying security to a control group, he does not find a meaningful increase in volatility. Also, Bessembinder and Seguin (1992) do not find that trading in the futures market significantly affects the volatility of the underlying asset. In another stream of literature, research has shown that derivatives can lead to higher levels of volatility in the underlying asset around expiration days (Samuelson, 1965, Stoll and Whaley, 1987, Hancock, 1993, Chow *et al.* 2003, and Illueca and LaFuente, 2006).

[2] Other existing studies have highlighted that bitcoin volatility can also be attributed to various types of price manipulation. See, for example, Gandal, Hamrick, Moore, and Oberman (2018).

In a number of both univariate and multivariate tests, we find that various measures of volatility increase significantly during the post-introduction period for Bitcoin. These results seem to support the ideas in Stein (1987) and suggest that the volatility of Bitcoin increases in response to the introduction of Bitcoin futures.

To our knowledge, both the theoretical and empirical literature has focused primarily on the impact of derivative introductions on underlying assets. Fewer studies have examined possible spillover effects. On one hand, the volatility of a group of related assets may decrease when derivatives for one of the assets are introduced. Here, speculation might increase for the treated asset but decrease for the other group of related assets resulting in a negative volatility spillover effect. On the other hand, if the initial group of related assets are difficult to value, then the introduction of derivatives might result in an improved ability to value the treated asset since observing another price for the derivative contract might assist in the pricing of the underlying, treated asset (Ross, 1976, and Phillips, 2011). Those other assets in the group (without tradable derivative contracts) might increase in volatility in response to the introduction of the derivatives on the underlying treated asset. The introduction may, therefore, result in positive, volatility spillover effects. Our study provides tests of potential spillover effects. In particular, we replicate our event study for 16 non-Bitcoin currencies. Interestingly, we find that volatility significantly increases for this group of cryptocurrencies. In fact, our multivariate tests show that the increase in non-Bitcoin currencies is greater than the increase in Bitcoin. These results seem to indicate that, in response to the introduction of Bitcoin futures, there are indeed positive, volatility spillover effects for non-Bitcoin currencies.[3]

The findings from our analysis contribute to the literature in two important ways. First, our analysis is the first to analyze the effect of the introduction of Bitcoin futures on the price stability of Bitcoin. Second, our findings highlight spillover effects by suggesting that while the volatility increase in Bitcoin was significant and meaningful, the increase in the volatility of non-Bitcoin currencies was even greater.

2. Data Description

The data used throughout the analysis comes from Coinmarketcap.com. The data consist of daily prices, daily volume, and daily market capitalization. We restrict our sample to the 17 most active and largest cryptocurrencies for the 120-day period surrounding the December 10th, 2017 introduction of Bitcoin futures by the CBOE. Therefore, our final sample includes 2,040 currency-day observations. Using closing prices, we calculate daily (percent) returns and estimate three measures of volatility. *SMA* is simple (20-day) moving average volatility and is calculated as the standard deviation of the returns from day t to t-20. *Range* is the difference between the daily high price and the daily low price scaled by the high-low midpoint. *Garch* is the square root of the conditional expected variance from fitting daily returns to a Garch(1,1) model.

Table 1 reports statistics that summarize the data used throughout the analysis. Panel A reports the summary statistics for the entire sample of 17 cryptocurrencies while Panel B shows

[3] Symitsi and Chalvatzis (2018) also examine potential spillover effects. However, this study examines shows that volatility spillovers occur from technology firms to Bitcoin.

the statistics for each of the cryptocurrencies individually. *SMA*, *Range*, and *Garch* have been defined previously. *Volume* is the average daily trading volume. *Illiq* is the Amihud (2002) measure of illiquidity and is calculated as the absolute value of daily returns scaled by daily dollar

Table 1 – Summary Statistics

The table reports statistics that summarize the data used throughout the analysis. Panel A reports the summary statistics for the entire sample of 17 cryptocurrencies while Panel B shows the statistics for each of the cryptocurrencies individually. SMA is simple (20-day) moving average volatility and is calculated as the standard deviation of the returns from day t to t-20. RANGE is the difference between the daily high price and the daily low price scaled by the high-low midpoint. GARCH is the square root of the conditional expected variance from fitting daily returns to a Garch(1,1) model. VOLUME is the average daily trading volume. ILLIQ is the Amihud (2002) measure of illiquidity and is calculated as the absolute value of daily returns scaled by daily dollar volume (in 100 million). VALUE is the average daily price of each cryptocurrency. MKT CAP is the average daily market capitalization. Panel C reports the correlation coefficients between each of the variables used in the analysis. *, **, and *** denote statistical significance at the 0.10, 0.05, and 0.01 levels, respectively.

Panel A. Summary Statistics for the Entire Sample							
	SMA	RANGE	GARCH	VOLUME	ILLIQ	VALUE	MKT CAP
	[1]	[2]	[3]	[4]	[6]	[7]	[8]
Mean	0.0938	0.1468	0.1008	1,025,279,601	0.2495	849.73	20,084,698,926
Std. Dev.	0.0554	0.1208	0.0493	2,694,538,940	1.3409	2709.43	47,535,418,688
Min	0.0211	0.0103	0.0031	50,124	0.0000	0.17	11,423,500
Median	0.0843	0.1167	0.0945	122,822,500	0.0010	30.10	2,935,540,000
Max	0.3928	1.7799	0.5497	23,840,900,000	28.6960	19497.40	326,141,000,000
Panel B. Summary Statistics by Cryptocurrency							
Bitcoin	0.0588	0.0980	0.0574	9,014,530,167	0.0000	10,778.87	180,151,075,833
bit_cash	0.1098	0.1538	0.1224	1,544,613,142	0.0000	1,512.94	25,446,420,750
bitcon	0.1228	0.1892	0.1511	19,752,692	0.8305	248.49	1,198,992,633
dash	0.0789	0.1143	0.0807	168,448,127	0.0001	698.05	5,409,635,167
ethereum	0.0578	0.1002	0.0699	2,652,933,300	0.0000	644.04	61,873,766,667
ether_CL	0.0868	0.1345	0.0922	394,728,612	0.0017	24.55	2,413,451,667
iota	0.1051	0.1788	0.1143	214,662,963	0.2548	2.15	5,970,532,142
litecoin	0.0792	0.1200	0.0902	824,476,023	0.0001	150.74	8,174,459,917
monero	0.0753	0.1260	0.0826	133,061,535	0.0004	237.46	3,673,602,583
nem	0.1368	0.1600	0.1097	59,082,707	1.2323	0.61	5,483,382,250
neo	0.0946	0.1508	0.1072	231,005,265	0.0015	66.71	4,233,297,417
numaire	0.1092	0.2205	0.1152	1,507,063	1.7174	22.27	28,598,646
omisego	0.0832	0.1436	0.1023	77,740,614	0.0132	12.31	1,249,171,075
qtum	0.1085	0.1465	0.1250	435,131,202	0.0027	28.65	2,096,134,242
ripple	0.1089	0.1431	0.1049	1,586,049,074	0.0393	0.84	32,374,543,667
stratis	0.0990	0.1772	0.1065	35,734,263	0.0867	8.89	874,629,708
waves	0.0796	0.1384	0.0830	36,296,479	0.0602	7.87	788,187,375
Panel C. Correlation Matrix							
SMA	1.0000	0.4242***	0.3854***	-0.0143	0.0786***	-0.1134***	-0.0707***
RANGE		1.0000	0.3933***	0.0434**	0.1184***	-0.0825***	-0.0676***
GARCH			1.0000	-0.1296***	0.1320***	-0.1890***	-0.1968***
VOLUME				1.0000	-0.0701***	0.8724***	0.9238***
ILLIQ					1.0000	-0.0579***	-0.0753***
VALUE						1.0000	0.9297***
MKTCAP							1.0000

volume (in 100 million). *Value* is the closing daily price of each cryptocurrency. *Mkt Cap* is the closing daily market capitalization.

Here, we find that for the average currency, *SMA* is 9.38%, *Range* is 14.68%, and *Garch* is 10.08%. The average currency also has an average daily volume of over 1 billion shares, illiquidity of .2495, a price (or value) of $849.73, and a market cap of $20.1 billion. Panel B shows the summary statistics for each of the cryptocurrencies separately.[4] Panel C reports pooled Pearson correlation coefficients. As expected, we find a strong, positive correlation between *SMA, Range*, and *Garch*. The other cross correlations are reported in the panel.

3. Empirical Results

3.1 Univariate Tests

We begin our analysis by examining the volatility of cryptocurrencies during the 120-day period surrounding the introduction of futures contracts. Results from our initial event study are reported in Table 2. Panel A reports the results for Bitcoin while Panel B reports the results for the other 16 cryptocurrencies. Both panels present results for the 60-day period "before" the introduction and the 60 days "after" the introduction. The difference between the after period and the before period are reported at the bottom of each panel with corresponding t-statistics.

Results for our volatility measures are reported in Columns [1] through [3]. We find a significant increase in all three measures of volatility. *SMA* increases by 0.0319; a difference that is significant at the 0.01 level. *Range* increases more than 0.03, which is also statistically significant. Similar results are found for *Garch*. In economic terms, the increase in *SMA* represents a 75% increase while the increases in *Range* and *Garch* represent a 48% and 17% increase, respectively. Columns [4] through [7] also report results for *Volume*, *Illiq*, *Value*, and *Mkt Cap*, respectively. In general, Panel A is consistent with the predictions of Stein (1987), which suggest that the introduction of derivatives will destabilize the underlying asset.

Panel B reports results for the other 16 cryptocurrencies in our sample and demonstrates the magnitude of the spillover effects. Here, we see a similar pattern as in Panel A with highly significant changes in volatility after the introduction of Bitcoin futures. For instance, *SMA* increases from 6.81 % to 12.38%. The difference is 5.57% and represents an 82% increase in volatility. Qualitatively similar results are found in the other measures of volatility.

3.2 Multivariate Analysis

Table 3 reports results for difference-in-difference regressions that estimate the following equation using pooled, currency-day data.

$$VOLATILITY_{i,t} = \beta_0 + \beta_1 Treatment_i + \beta_2 Post_t + \beta_3 Treatment_i \times Post_t + \beta_4 Ln(Value_{i,t}) + \beta_5 Ln(MktCap_{i,t}) + \beta_6 Ln(Volume_{i,t}) + \beta_7 Ln(Illiq_{i,t}) + \varepsilon_{i,t} \quad (1)$$

[4] We note that Panel B has abbreviated some of the currencies. For instance, Bit_cash is Bitcoin Cash; Bitcoin is Bitconnect; Ether_CL is Ethereum Classic, etc.

Table 2 – Event Study Surrounding the Introduction of CBOE Bitcoin Futures

The table reports the results from a simple event study. Using the 120-day period surrounding the introduction of CBOE Bitcoin future contracts, which occurred on December 17th, 2017. Panel A reports the results for Bitcoin while Panel B reports the results for the other 16 cryptocurrencies. The table report the average of daily variables described in the top row for the "Before" period (October 18th, 2017 to December 16th, 2017) and the "After" period (December 17th, 2017 to February 14th, 2018). The bottom row of each panel reports the difference between the After period and the Before period with a corresponding t-statistics in parentheses. SMA is simple (20-day) moving average volatility and is calculated as the standard deviation of the returns from day t to t-20. RANGE is the difference between the daily high price and the daily low price scaled by the high-low midpoint. GARCH is the square root of the conditional expected variance from fitting daily returns to a Garch(1,1) model. VOLUME is the average daily trading volume. ILLIQ is the Amihud (2002) measure of illiquidity and is calculated as the absolute value of daily returns scaled by daily dollar volume. VALUE is the average daily price of each cryptocurrency. MKT CAP is the average daily market capitalization. We note that MKTCAP and VOLUME are denoted in billions. *, **, and *** denote statistical significant at the .10, .05, and the .01 level, respectively.

Panel A. Bitcoin							
	SMA	RANGE	GARCH	VOLUME	ILLIQ	VALUE	MKTCAP
	[1]	[2]	[3]	[4]	[5]	[6]	[7]
Before	0.0428	0.0792	0.0530	4.7149	0.0149	7,946.50	129.60
After	0.0747	0.1168	0.0619	13.3100	0.0038	13,611.20	230.70
After – Before	0.0319***	0.0376***	0.0089**	8.5951***	-0.0111***	5,664.70***	101.10***
	(19.68)	(3.72)	(2.40)	(11.99)	(-5.75)	(10.56)	(11.76)
Panel B. Non-Bitcoin Currencies							
Before	0.0681	0.1118	0.0929	0.2411	0.3797	141.40	4.89
After	0.1238	0.1878	0.1142	0.8108	0.1504	316.90	15.27
After – Before	0.0557***	0.0760***	0.0214***	0.5697***	-0.2293***	175.50***	10.38***
	(24.97)	(14.22)	(9.71)	(11.00)	(-3.65)	(8.39)	(11.74)

The dependent variable is VOLATILITY, which is either *SMA*, *Range*, or *Garch*. The independent variables include the following: *Treatment* is equal to unity if currency *i* is Bitcoin – zero otherwise. *Post* is equal to one on days after December 19th, 2017 – zero otherwise. *Treatment*×*Post* is the interaction between the two variables. Other control variables include the following. *Ln(Value)* is the natural log of the daily price of the currency *i*. *Ln(MktCap)* is the natural log of the daily market capitalization for each currency. *Ln(Volume)* is the natural log of the daily volume. *Ln(Illiq)* is the natural log of the daily Amihud illiquidity.[5] We report corresponding t-statistics, which are obtained from White (1980) robust standard errors.

Columns [1] and [2] report results for regressions where *SMA* is the dependent variable. Column [1] only includes indicator variables for *Treatment*, *Post*, and the interaction between *Treatment* and *Post* while column [2] reports the full specification. In column [1], the coefficient on the interaction between *Treatment*×*Post* is negative and significant suggesting that relative to non-Bitcoin currencies, Bitcoin's volatility decreased (or increased less) during the post-introduction period. Stated differently, non-Bitcoin currencies had a larger increase in volatility than Bitcoin itself during the period following the introduction of Bitcoin futures. It is also worth noting that all of our control variables are generally significant with the expected signs. We also note that Columns [3] through [6] provide results that are qualitatively similar those in the first

[5] Dyhrberg, Folley, and Svec (2018) describe how trading activity and create volatility in Bitcoin. Therefore, we include these liquidity variables as additional control variables. Additionally, Chaim and Laurini (2018) examine volatility jumps in Bitcoin and find that volatility was highest in 2013 and 2014, when trading activity seemed to be the highest.

Table 3 – Difference-In-Difference Regressions

The table reports the result from estimating the following equation using currency-day observations for the 120-day period surrounding the introduction of CBOE Bitcoin Futures.

$$VOLATILITY_{i,t} = \beta_0 + \beta_1 Treatment_i + \beta_2 Post_t + \beta_3 Treatment_i \times Post_t + \beta_4 Ln(Value_{i,t}) + \beta_5 Ln(MktCap_{i,t}) + \beta_6 Ln(Volume_{i,t}) + \beta_7 Ln(Illiq_{i,t}) + \varepsilon_{i,t}$$

The dependent variable is VOLALITY and is measured as either SMA (columns [1] and [2]), RANGE (columns [3] and [4]), and GARCH (columns [5] and 6]). The independent variables include the following variables: Treatment is equal to unity if currency *i* is Bitcoin – zero otherwise. Post is equal to one on days after December 16th, 2017 – zero otherwise. Treatment×Post is the interaction between the two variables. Ln(Value) is the natural log of the daily price of the currency *i*. Ln(MktCap) is the natural log of the daily market capitalization for each currency. Ln(Volume) is the natural log of the daily volume. Ln(Illiq) is the natural log of the daily Amihud illiquidity. Under each coefficient, we report the corresponding t-statistic, which are obtained from White (1980) robust standard errors. *, **, and *** denote statistical significant at the .10, .05, and the .01 level, respectively.

	SMA		RANGE		GARCH	
	[1]	[2]	[3]	[4]	[5]	[6]
Intercept	0.0681***	0.0435**	0.1118***	0.1022**	0.0929***	0.1206***
	(58.93)	(2.54)	(37.29)	(2.38)	(67.96)	(7.16)
Treatment	-0.0253***	-0.0240***	-0.0326***	-0.0874***	-0.0399***	-0.0413***
	(-15.23)	(-4.66)	(-4.41)	(-6.99)	(-13.73)	(-6.52)
Post	0.0557***	0.0558***	0.0760***	0.0671***	0.0214***	0.0224***
	(24.98)	(21.93)	(14.23)	(14.26)	(9.72)	(8.76)
Treatment×Post	-0.0238***	-0.0352***	-0.0384***	-0.0999***	-0.0124***	-0.0243***
	(-8.66)	(-12.84)	(-3.39)	(-10.08)	(-2.88)	(-5.83)
Ln(Value)		0.0016*		0.0234***		0.0043***
		(1.83)		(10.31)		(4.54)
Ln(MktCap)		-0.0073***		-0.0545***		-0.0097***
		(-5.28)		(-12.76)		(-6.12)
Ln(Volume)		0.0121***		0.0740***		0.0117***
		(8.43)		(17.91)		(6.08)
Ln(Illiq)		0.0077***		0.0417***		0.0082***
		(7.86)		(14.86)		(7.45)
Adjusted R^2	0.2664	0.3272	0.1035	0.4020	0.0917	0.1647
Robust SEs	Yes	Yes	Yes	Yes	Yes	Yes
N	2,040	2,040	2,040	2,040	2,040	2,040

two columns suggesting that our results are robust to alternative measures of volatility (RANGE and GARCH).[6]

4. Conclusion

In financial markets, the presence of derivatives may result in both positive and negative externalities. Some existing theory suggests that the presence of derivatives will reduce the volatility of asset prices while other theory suggests that derivatives will promote greater volatility. Using the cryptocurrency market and the introduction of Bitcoin futures as our natural experiment, we test between the competing ideas in the existing literature. Results from our tests show that Bitcoin volatility significantly increases during the post-introduction period. The results are both economically and statistically significant. These results seem to provide some consistency with

[6] We conduct a series of robustness tests. In particular, we replicate our entire analysis focusing on Bitcoin family currencies, which include Bitcoin, Litecoin, and Bitcoin Cash, as the treated currencies. We are able to find remarkably similar results suggesting that the identification of the treatment is robust to other Bitcoin-related currencies.

Stein (1987) and suggest that the presence of derivative markets can enhance volatility in underlying asset prices. In addition to these initial set of tests, we also develop and test the hypothesis that the introduction of Bitcoin futures may result in positive spillover effects for other cryptocurrencies. Interestingly, we find that while Bitcoin volatility increases during the post-introduction period, the volatility of non-Bitcoin currencies increases even more. These results are robust to different measures of volatility as well as controls for other factors.

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