Economics Bulletin

Volume 40, Issue 1

Comovement in the Cryptocurrency Market

Benjamin Blau
Utah State University

Todd Griffith
Utah State University

Ryan Whitby
Utah State University

Abstract

This study examines the comovement between 17 of the most active cryptocurrencies. We are unable to statistically reject the presence of perfect comovement between Bitcoin and six of the 16 non-Bitcoin cryptocurrencies. Consistent with the friction-based explanation for the presence of comovement, once the CBOE introduced futures contracts on Bitcoin, we find that all 16 cryptocurrencies comove with Bitcoin. These results suggest that introducing futures contracts improves the informational environment of the entire cryptocurrency market, which helps explain the unusual comovement in the cryptocurrency market.

Citation: Benjamin Blau and Todd Griffith and Ryan Whitby, (2020) "Comovement in the Cryptocurrency Market", *Economics Bulletin*, Volume 40, Issue 1, pages 448-455
Contact: Benjamin Blau - ben.blau@usu.edu, Todd Griffith - todd.griffith@usu.edu, Ryan Whitby - ryan.whitby@usu.edu.
Submitted: September 18, 2019. **Published:** February 07, 2020.

1. Introduction

In general, asset pricing theory asserts that comovement in the prices of different assets can be explained as a reflection of comovement in the assets' fundamentals (Barberis, Shleifer, and Wurgler (2005)). What happens, however, if an asset lacks fundamentals? Without underlying cash flows or policies of a specific country, government, or central bank, cryptocurrencies provide an interesting setting to examine comovement given the lack of fundamentals. In this study, we examine the comovement between 17 of the most active cryptocurrencies. Given its popularity, relative to the other currencies, Bitcoin is the largest and most active cryptocurrency. When examining the comovement of the 16 non-Bitcoin currencies to Bitcoin, we find a remarkable level of comovement. For instance, we are unable to reject the presence of perfect comovement in six of the 16 non-Bitcoin currencies. At first glance, these results are puzzling and suggest that comovement can be explained by something other than correlated fundamentals among assets.

During our time period, which extends almost 14 months across 2017 and 2018, a major innovation in the cryptocurrency market occurred. On December 10th, 2017, the Chicago Board Options Exchange (CBOE) introduced futures contracts on Bitcoin. Antoniou and Holmes (1995) show that the introduction of futures contracts improves the informational environment in the spot market. Likewise, the theory in Ross (1976) discusses how introducing derivatives increases the overall informational efficiency of markets. Danthine (1978) comes to similar conclusions as the presence of derivatives seems to improve the accuracy of prices. Perhaps an alternative explanation for the presence of comovement is that a particular market lacks a sufficiently strong information environment. This idea is spelled out nicely in Veldkamp (2006), who discusses how informational frictions might explain comovement. In the framework of our study, the presence of Bitcoin futures and the subsequent improvement in the information environment for Bitcoin might increase the level of comovement that we observe in the non-Bitcoin currencies. By allowing for better risk management through hedging activities as well as the potential for arbitrage, futures contracts may improve the price efficiency of Bitcoin. As such, prices of other cryptocurrencies may become more prone to comove with Bitcoin once futures become available. To test this assertion, we examine the comovement of various cryptocurrencies surrounding the introduction of bitcoin-based futures contracts.

Our results show that in the days after the CBOE introduced futures contracts on Bitcoin, the observed comovement between cryptocurrencies and Bitcoin markedly increases. In fact, during the post-introduction period, we are unable to statistically reject the presence of perfect comovement for each of the 16 non-Bitcoin currencies. These findings support the idea that in certain markets without much in the way of fundamentals, the presence of futures contracts, and the subsequent improvement in the information environment associated with these contracts, might generate higher levels of comovement among assets in a particular market. These findings point to the informational benefits of derivatives markets and contribute to the existing literature regarding these benefits (Ross (1976), Figlewski and Webb (1993), Antoniou and Holmes (1995), Chakravarty, Gulen, and Mayhew (2005), Pan and Poteshman (2006), Chang, Hseih, and Wang (2010), Johnson and So (2011), and Blau, Nguyen, and Whitby (2014)). Furthermore, our findings contribute to the comovement literature by highlighting the importance of the information environment in explaining the presence of comovement (Barberis and Shleifer (2003) and Veldkamp (2006)).

2. Data Description

The data used throughout the analysis comes from Coinmarketcap.com and consists of daily prices, volume, and market capitalization. The data includes the 17 most active, and largest, cryptocurrencies for the period from January 1st, 2017 to February 20th, 2018. The total market capitalization for these currencies during this time period was nearly $167 billion. As a comparison, during our sample time period, only 45 firms in the S&P 500 had a market capitalization of more than $100 billion. There exist 416 trading days in our sample, but only 10 of the 17 cryptocurrencies are traded each day during that period. The remaining currencies began trading in the middle of the sample time period.

Our analysis includes several variables that we compute for each cryptocurrency. *Value* is the daily price of each cryptocurrency (denominated in U.S. dollars). *MktCap* is the daily market capitalization or the price times number of coins outstanding. *Volume* is the daily trading volume for each of the cryptocurrencies. *Turn* is the daily turnover, which is the ratio of daily trading volume scaled by coins outstanding. *Volt* is the 20-day simple moving average (SMA) standard deviation of daily percent changes in price. *Range* is the difference between the intraday high price and the intraday low price scaled by the high-minus-low midpoint.

Table 1 reports statistics that summarize our sample. We report the averages of the variables discussed above for each of the 17 cryptocurrencies in our sample. In particular, each row in the table reports the average daily *Value*, the average daily *MktCap*, etc., for each currency. As seen in Panel A, the average price for Bitcoin during our sample time period was $4,930 while the average market capitalization was nearly $82 billion. We also find that the average daily volume for Bitcoin was more than 3.5 billion coins while the average daily turnover was 210.58. We also find that the average volatility for Bitcoin was 4.78% during our sample time period and the average range-based volatility was 7%. We report these statistics for each of the cryptocurrencies. Panel B also provides Pearson correlation coefficients for the pooled (currency-day) sample. The first row suggests that the cryptocurrency price is positively correlated with market capitalization, volume, and turnover and negatively correlated with the SMA volatility and range-based volatility. We also find that SMA volatility is negatively related to trading volume and turnover. In contrast, range-based volatility is directly correlated to volume and uncorrelated with turnover.

Table 1. Summary Statistics

This table reports statistics that describe the sample used throughout the analysis. The sample consists of 17 of the most active cryptocurrencies. The sample time period extends from January 1, 2017, to February 20, 2018. *Value* is the average price of each cryptocurrency (denominated in U.S. dollars). *MktCap* is the average market capitalization or the price times number of coins outstanding. *Volume* is the average daily trading volume for each of the cryptocurrencies. *Turn* is the average daily turnover, which is the ratio of daily trading volume scaled by coins outstanding. *Volt* is the 20-day simple moving average standard deviation of daily percent changes in price. *Range* is the difference between the intraday high price and the intraday low price scaled by the high-minus-low midpoint. Panel A reports the summary statistics while panel B shows the correlation coefficients for the variables used throughout the analysis. P-values are reported in brackets. *, **, and *** denote statistical significance at the 0.10, 0.05, and 0.01 levels, respectively.

Panel A. Summary Statistics

	Value	MktCap	Volume	Turn	Volt	Range
	[1]	[2]	[3]	[4]	[5]	[6]
Bitcoin	4,930.54	81,711,555,048	3,501,712,058	210.58	0.0478	0.0700
Bitcoin Cash	1,113.15	19,153,041,330	1,074,103,977	70.89	0.1180	0.1630
BitConnect	107.12	564,840,978	7,871,617	1.90	0.1129	0.1621
Dash	318.17	2,430,230,263	73,955,710	9.98	0.0759	0.1039
Ethereum	321.04	30,448,039,909	1,205,059,637	12.79	0.0669	0.0920
Ethereum Classic	14.85	1,421,705,918	187,956,528	2.00	0.0815	0.1069
iota	1.43	3,799,617,976	112,630,110	0.04	0.1070	0.1656
Litecoin	68.30	3,653,208,608	411,646,373	8.02	0.0759	0.0968
Monero	105.91	1,617,995,962	56,826,122	3.80	0.0751	0.1055
NEM	0.39	2,479,453,805	23,536,010	0.01	0.1040	0.1344
NEO	28.81	1,752,531,504	96,695,506	1.66	0.1164	0.1512
Numeraire	24.73	33,053,042	1,520,028	1.25	0.1307	0.2151
OmiseGO	10.50	1,039,818,718	67,416,381	0.71	0.1173	0.1609
Qtum	19.42	1,506,905,314	232,092,282	4.13	0.1214	0.1576
Ripple	0.38	14,031,498,315	582,078,096	0.02	0.0997	0.1168
Stratis	4.91	499,696,490	16,037,974	0.17	0.1034	0.1609
Waves	4.08	406,900,166	13,079,482	0.13	0.0810	0.1300

Panel B. Correlation Matrix

	Value	MktCap	Volume	Turn	Volt	Range
Value	1.0000	0.9274***	0.8654***	0.9276***	-0.1088***	-0.0640***
		[<.0001]	[<.0001]	[<.0001]	[<.0001]	[<.0001]
MktCap		1.0000	0.9179***	0.8612***	-0.0828***	-0.0515***
			[<.0001]	[<.0001]	[<.0001]	[<.0001]
Volume			1.0000	0.9327***	-0.0259**	0.0480***
				[<.0001]	[0.0416]	[0.0002]
Turn				1.0000	-0.0559***	0.0096
					[<.0001]	[0.4515]
Volt					1.0000	0.4106***
						[<.0001]
Range						1.0000

3. Empirical Results

In this section, we test for comovement between the values of Bitcoin and the 16 other large cryptocurrencies. Second, we examine the comovement between Bitcoin and other cryptocurrencies surrounding the introduction of Bitcoin futures. To examine the comovement between Bitcoin's daily return and each of the 16 non-Bitcoin cryptocurrencies, we estimate the following regression equation:

$$R_{i,t} = \alpha + \phi Bitcoin\ Return_t + \varepsilon_{i,t}\ , \tag{1}$$

where the dependent variable, $R_{i,t}$, is the daily return on one of 16 non-Bitcoin cryptocurrencies and the independent variable is Bitcoin's daily return. We report the results of estimating eq. (1) in Table 2 with test-statistics in parenthesis obtained from White (1980) robust standard errors.

In Column [2] of Table 2, we find that the values of each of the 16 cryptocurrencies are directly related to the values of Bitcoin. For example, the positive and significant coefficient in the Bitcoin Cash regression of 0.4225, indicates that we reject the null hypothesis that the prices of Bitcoin and Bitcoin Cash are unrelated. We draw nearly identical conclusions for the remaining 15 cryptocurrencies. To perform a more direct test of comovement, we analyze if the coefficient ϕ is statistically different from unity. If the coefficient is not statistically different from one, then we fail to reject the null hypothesis of perfect comovement between the two observed cryptocurrencies. Interestingly, in Column [3] we cannot reject perfect comovement for six of the 16 cryptocurrencies. For instance, the coefficient on BitConnect is not statistically different from one, with a robust t-statistic of 0.73. We find similar results for IOTA (t-statistic = -0.85), OmiseGo (t-statistic = -1.16), Qtum (t-statistic = -0.24), Stratis (t-statistic = -0.95), and Waves (t-statistic = -1.36). These initial results suggest that significant comovement exists across assets in the cryptocurrency market.

The analysis thus far shows that cryptocurrencies comove with Bitcoin. In an attempt to distinguish between comovement attributable to market frictions and comovement attributable to sentiment, we examine the change in the comovement of cryptocurrencies around the introduction of Bitcoin-based futures contracts. The introduction of futures contracts on Bitcoin provides an innovation in the coin's information environment (Antoniou and Holmes (1995)). To the extent that this is true, and that comovement between cryptocurrencies is related to information - or trading-frictions, then we expect to find a decrease in comovement between Bitcoin and other cryptocurrencies after the introduction of futures. Accordingly, we estimate the following regression equation:

$$R_{i,t} = \alpha + \phi_1 Bitcoin\ Return_t + \phi_2 Post_t + \phi_3 Bitcoin\ Return_t \times Post_t + \varepsilon_{i,t}\ , \tag{2}$$

where the dependent variable is the percent change in daily prices for each non-Bitcoin cryptocurrency on day *t*. *Bitcoin Return* is equal to the daily return on Bitcoin. *Post* is equal to one if the observation is on or after December 10th, 2017 – the day Bitcoin futures were introduced – and zero otherwise. The interaction term helps us understand whether, relative to the pre-introduction period, comovement changes during the post-introduction period. Determining whether or not comovement exists during the post-introduction period is found by subtracting one from the sum of ϕ_1 and ϕ_3. Table 3 details the results of this analysis.

The table shows that ϕ_3 is positive and reliably significant for seven of the 16 non-Bitcoin currencies. More importantly, the results in column [5] of Table 3 suggest that perfect comovement cannot be rejected for any of the 16 non-Bitcoin currencies. Said differently, the sum of the coefficients ϕ_1 and ϕ_3 are statistically close to one for each of the 16 currencies in question. For example, the sum of the coefficients for Bitcoin Cash is 0.9434, which is statistically close to one (t-statistic = -0.14). Likewise, the sum of the coefficients for Waves is 0.9518, which is not reliably different from one (t-statistic = -0.24). These findings are striking and suggest that when Bitcoin futures become available and the information environment improves, greater comovement in the cryptocurrency market exists.

Table 2. Comovement with Bitcoin

The table reports the results from estimating the following equation using simple OLS for each of the 16 (non-Bitcoin) cryptocurrencies:

$$R_{i,t} = \alpha + \phi Bitcoin\ Return_t + \varepsilon_{i,t}\ .$$

The dependent variable is the percent change in daily prices for each cryptocurrency from day *t-1* to day *t*. The independent variable is the percent change in daily prices for Bitcoin. The table reports the coefficient estimates with corresponding White (1980) robust t-statistics – testing the difference between the coefficient and zero. Column [3] reports the difference between the coefficient estimate ϕ and unity. Underneath these differences, a t-statistic (using White (1980) robust standard errors) tests the difference between the coefficient and one. *, **, and *** denote statistical significant at the 0.10, 0.05, and the 0.01 levels, respectively.

	α	ϕ	$\phi - 1$	Adjusted R^2	N
	[1]	[2]	[3]	[4]	[5]
Bitcoin Cash	0.0094	0.4225**	-0.5775***	0.0353	211
	(1.03)	(2.52)	(3.44)		
BitConnect	0.0105	1.1334***	0.1334	0.1929	396
	(1.65)	(6.23)	(0.73)		
Dash	0.0088**	0.6053***	-0.3947***	0.1484	416
	(2.32)	(6.28)	(-4.10)		
Ethereum	0.0099***	0.5928***	-0.4072***	0.1776	416
	(2.92)	(6.78)	(-4.66)		
Ethereum	0.0066	0.6994***	-0.3006***	0.1708	416
Classic	(1.65)	(6.54)	(-2.81)		
IOTA	0.0044	0.8863***	-0.1137	0.2124	252
	(0.69)	(6.59)	(-0.85)		
Litecoin	0.0077**	0.7344***	-0.2656***	0.1927	416
	(1.99)	(7.73)	(-2.80)		
Monero	0.0050	0.7526***	-0.2474***	0.2337	416
	(1.42)	(9.18)	(-3.02)		
NEM	0.0135**	0.6490***	-0.3510**	0.0665	416
	(1.99)	(3.77)	(-2.04)		
NEO	0.0191***	0.6994**	-0.3006**	0.0702	416
	(3.01)	(5.91)	(-2.54)		
Numeraire	0.0009	0.6360***	-0.3640**	0.0682	242
	(0.10)	(3.86)	(-2.21)		
OmiseGO	0.0161**	0.8020***	-0.1980	0.1396	221
	(2.01)	(4.70)	(-1.16)		
Qtum	0.0064	0.9667***	-0.0333	0.1810	272
	(0.88)	(6.98)	(-0.24)		
Ripple	0.0164**	0.4634***	-0.5366***	0.0280	416
	(2.44)	(4.59)	(-5.32)		
Stratis	0.0111**	0.8977***	-0.1023	0.1774	416
	(2.23)	(8.32)	(-0.95)		
Waves	0.0053	0.8837***	-0.1163	0.2870	416
	(1.54)	(10.34)	(-1.36)		

Table 3. Comovement with Bitcoin Surrounding the Introduction of Bitcoin Futures

The table reports the results from estimating the following equation using simple OLS for each of the 16 non-Bitcoin cryptocurrencies:

$$R_{i,t} = \alpha + \phi_1 Bitcoin\ Return_t + \phi_2 Post_t + \phi_3 Bitcoin\ Return_t \times Post_t + \varepsilon_{i,t}\ .$$

The dependent variable is the percent change in daily prices for each cryptocurrency from day *t-1* to day t. The independent variables include the following: $Bitcoin\ Return$ is the percent change in daily prices for Bitcoin. $Post$ is an indicator variable equal to one if day t is on or after December 17, 2017 – the day Bitcoin futures were introduced. We also include the interaction between the two independent variables. The table reports the coefficient estimates with corresponding White (1980) robust t-statistics – testing the difference between the coefficient and zero. Column [5] reports the difference between the coefficient estimate ϕ_3 and unity. Underneath these differences, a t-statistic (using White (1980) robust standard errors) tests the difference between the coefficient and one. *, **, and *** denote statistical significant at the 0.10, 0.05, and the 0.01 levels, respectively.

	α	ϕ_1	ϕ_2	ϕ_3	$(\phi_1+\phi_3) - 1$	Adj. R^2	N
	[1]	[2]	[3]	[4]	[5]	[6]	[7]
Bitcoin	0.0163	-0.0447	-0.0068	0.9881***	-0.0566	0.0803	211
Cash	(1.26)	(-0.17)	(-0.39)	(3.22)	(-0.14)		
BitConnect	0.0208***	0.8336***	-0.0421*	0.8284*	0.6620	0.2254	396
	(3.60)	(6.78)	(-1.84)	(1.81)	(1.40)		
Dash	0.0107**	0.4756***	-0.0050	0.4116**	-0.1128	0.1596	416
	(2.52)	(3.87)	(-0.55)	(2.39)	(-0.53)		
Ethereum	0.0096**	0.5218***	0.0048	0.2389	-0.2393	0.1806	416
	(2.47)	(4.51)	(0.59)	(1.53)	(-1.23)		
Ethereum	0.0065	0.5838***	0.0058	0.3857*	-0.0305	0.1788	416
Classic	(1.48)	(4.47)	(0.57)	(1.91)	(-0.13)		
IOTA	0.0078	0.9012***	-0.0124	-0.0606	-0.1594	0.2087	252
	(0.96)	(4.48)	(-1.06)	(-0.25)	(-0.51)		
Litecoin	0.0079*	0.5774***	0.0062	0.5205***	0.0979	0.2106	416
	(1.81)	(4.96)	(0.55)	(2.78)	(0.44)		
Monero	0.0049	0.6616***	0.0043	0.3028*	-0.0356	0.2386	416
	(1.29)	(6.56)	(0.48)	(1.94)	(-0.19)		
NEM	0.0153*	0.4926**	-0.0033	0.5010*	-0.0064	0.0708	416
	(1.87)	(2.07)	(-0.22)	(1.76)	(-0.02)		
NEO	0.0181**	0.6565***	0.0080	0.1537	-0.1898	0.0670	416
	(2.49)	(4.33)	(0.61)	(0.69)	(-0.70)		
Numeraire	-0.0016	0.5710**	0.0105	0.1814	-0.2476	0.0631	242
	(-0.13)	(2.30)	(0.60)	(0.57)	(-0.61)		
OmiseGO	0.0163	0.7179***	0.0022	0.2086	-0.0735	0.1342	221
	(1.45)	(2.75)	(0.15)	(0.68)	(-0.18)		
Qtum	-0.0008	0.8827***	0.0299	0.2787	0.1614	0.1889	272
	(-0.11)	(5.08)	(1.58)	(0.99)	(0.49)		
Ripple	0.0135**	0.3681***	0.0217	0.3489	-0.2830	0.0305	416
	(1.97)	(3.36)	(1.05)	(1.56)	(-1.14)		
Stratis	0.0122**	0.8521***	-0.0041	0.1405	-0.0074	0.1745	416
	(2.18)	(6.41)	(-0.34)	(0.63)	(-0.03)		
Waves	0.0061	0.8513***	-0.0026	0.1005	-0.0482	0.2844	416
	(1.57)	(7.83)	(-0.29)	(0.60)	(-0.24)		

4. Conclusion

The extant theoretical literature suggests that the presence of comovement is explained by comovement in fundamentals. Without much in the way of fundamentals, this study still shows a remarkable level of comovement in the cryptocurrency market. In particular, out of 16 non-Bitcoin currencies, we find that for six of the cryptocurrencies, we are unable to statistically reject the presence of perfect comovement with Bitcoin. These findings suggest that perhaps comovement in certain markets is explained by a lack of a sound information environment. To test this possibility, we examine the comovement of the 16 non-Bitcoin cryptocurrencies surrounding the introduction of CBOE Bitcoin futures contracts. Prior research shows that the introduction of futures improves the informational efficiency and the overall information environment of underlying assets in the spot market (see Ross (1976) and Antoniou and Holmes (1995)). In the framework of our study, if the presence of futures contracts leads to an improvement in the information environment of Bitcoin, then comovement between Bitcoin and the non-Bitcoin currencies should increase. Results show that, once Bitcoin futures become available, comovement markedly increases. For instance, during the post-introduction period, we are unable to statistically reject the presence of perfect comovement in all 16 non-Bitcoin currencies. These findings contribute to the literature on comovement by highlighting the importance of the information environment in explaining comovement in asset markets. The results also point to the informational benefits associated with the presence of derivative contracts.

References

Barberis, N. and Shleifer, A., 2003. Style investing. *Journal of Financial Economics*, 68(2), pp.161-199.

Barberis, N., Shleifer, A. and Wurgler, J., 2005. Comovement. *Journal of Financial Economics*, 75(2), pp.283-317.

Boyer, B.H., 2011. Style-Related Comovement: Fundamentals or Labels? *The Journal of Finance*, 66(1), pp.307-332.

Brockman, P., Liebenberg, I. and Schutte, M., 2010. Comovement, information production, and the business cycle. *Journal of Financial Economics*, 97(1), pp.107-129.

Chen, H., Singal, V. and Whitelaw, R.F., 2016. Comovement revisited. *Journal of Financial Economics*, *121*(3), pp.624-644.

Greenwood, R., 2007. Excess comovement of stock returns: Evidence from cross-sectional variation in Nikkei 225 weights. *The Review of Financial Studies*, 21(3), pp.1153-1186.

Greenwood, R.M. and Sosner, N., 2007. Trading patterns and excess comovement of stock returns. *Financial Analysts Journal*, 63(5), pp.69-81.

Hameed, A., Morck, R., Shen, J. and Yeung, B., 2015. Information, analysts, and stock return comovement. *The Review of Financial Studies*, 28(11), pp.3153-3187.

Kasch, M. and Sarkar, A., 2014. Is there an S&P 500 index effect? *Federal Reserve Bank of New York Staff Reports.*

Kumar, A. and Lee, C., 2006. Retail investor sentiment and return comovements. *The Journal of Finance*, 61(5), pp.2451-2486.

Pindyck, R.S. and Rotemberg, J.J., 1993. The comovement of stock prices. *The Quarterly Journal of Economics*, 108(4), pp.1073-1104.

Pindyck, R.S. and Rotemberg, J.J., 1988. The excess co-movement of commodity prices. Working Paper, Sloan School of Management, M.I.T.

Pirinsky, C. and Wang, Q., 2006. Does corporate headquarters location matter for stock returns? *The Journal of Finance*, 61(4), pp.1991-2015.

Tang, K. and Xiong, W., 2012. Index investment and the financialization of commodities. *Financial Analysts Journal*, 68(5), pp.54-74.

Veldkamp, L.L., 2006. Information markets and the comovement of asset prices. *The Review of Economic Studies*, 73(3), pp.823-845.

Vijh, A.M., 1994. S&P 500 trading strategies and stock betas. *The Review of Financial Studies*, 7(1), pp.215-251.

Von Drathen, C., 2014. Is there really excess comovement? Causal evidence from FTSE 100 index turnover. Working Paper, LSE.

White, H., 1980. A heteroskedasticity-consistent covariance matrix estimator and a direct test for heteroskedasticity. *Econometrica: Journal of the Econometric Society*, pp.817-838.