Price dynamics and speculative trading in bitcoin

Benjamin M. Blau

Department of Economics and Finance, Huntsman School of Business, Utah State University, 3565 Old Main Hill, Logan, UT, 84341, United States

ABSTRACT

Few innovations in the money markets have brought more attention by regulators and policy makers than the digital currency Bitcoin. However, few studies in the literature have examined the price dynamics of Bitcoin. Besides providing an exploratory glace at the value and volatility of the Bitcoin across time, we also test whether the unusual level of Bitcoin's volatility is attributable to speculative trading. Results in this study do not find that, during 2013, speculative trading contributed to the unprecedented rise and subsequent crash in Bitcoin's value nor do we find that speculative trading is directly associated with Bitcoin's unusual level of volatility.

1. Introduction

With the exception of perhaps currency derivatives, few financial innovations in money markets have drawn more attention by regulators and policy makers than the advent of the digital currency Bitcoin. Unregulated by governments, Bitcoin has become popular for both consumers and retailers as its value has increased from a few cents to as high as $1132.26 during the recent past. The popularity of Bitcoin by retailers might be due to lower transaction fees relative to other credit card processors. Bitcoin's popularity among consumers might be related to its unregulated structure or the privacy afforded by its anonymity. For these reasons, the U.S. Senate recently held hearings regarding potential risks associated with Bitcoin.[1] Amidst all of this interest, surprisingly few academic studies have explored Bitcoin's exchange rate dynamics and its functionality as a medium of exchange. The objective of this study is to take a step in this direction.

The objective of this study is twofold. First, we seek to provide some stylized facts about the price dynamics of Bitcoin. Second, and perhaps more interesting, we test the hypothesis that speculative trading in Bitcoin is responsible for its unusual level of volatility. The volatility of the digital currency might question whether or not Bitcoin functions as currency. While Bitcoin has certainly been used as medium of exchange for many consumers thus far, others have raised concerns that Bitcoin is less of a currency and more of a speculative investment.[2] Prior research suggests that speculation can lead to a destabilization of asset prices (Hart and Kreps, 1986; Stein, 1987). To the extent that Bitcoin volatility is indeed induced by speculative trading, such trading may reduce its role as a viable currency. Approximating speculative trading is a difficult task given that the motives to trade are not observed. However, Llorente, Michaely, Saar, and Wang (2002), provide an intuitive measure of speculative trading that captures the level of volume-induced return autocorrelation. Using this measure, we test the hypothesis that the unusually high volatility observed in Bitcoin is attributable to speculative trading.[3]

E-mail address: ben.blau@usu.edu.

[1] During the 2013 Senate Hearing, Senator Thomas R. Carper suggest that digital currencies such as Bitcoin, which are untraceable, can be used to fund criminal activity such as the distribution of weapons, child pornography, and murder-for-hire.

[2] See, for example, the following two articles in the New York Times. http://www.nytimes.com/2013/04/15/opinion/krugman-the-antisocial-network.html http://krugman.blogs.nytimes.com/2013/12/28/bitcoin-is-evil/

[3] Throughout this study, we estimate volatility following the breadth of literature related to generalized ARCH models. See, for example, Engle (1982), Bollerslev (1986), and Engle and Kroner (1995).

Results in this study show that the value of Bitcoin remained well below $20 from the start of our time period (September 2010) to the beginning of 2013. In 2013, the value of Bitcoin was as low as $13 and as high as $1132. In the months that followed the spike in Bitcoin's value, the digital currency lost approximately 60% of its value. These price dynamics seem to indicate the presence of a bubble in Bitcoin (Blanchard, 1979; Flood and Hodrick, 1990; Scheinkman and Xiong, 2003). The estimated volatility for Bitcoin during our sample time period is nearly 6% which is nearly twice as large as the average volatility of 51 other currencies. When examining speculative trading in Bitcoin, to our surprise, we do not find an unusual amount of this type of trading during our sample time period. In fact, during the latter part of 2013–Bitcoin's bubble period − we do not observe any speculative trading according to the methods of Llorente et al. (2002).

Observing low levels of speculative trading during our sample time period is not tantamount to identifying the relationship between speculative trading and volatility. Additional tests show that speculative trading is not positively related to Bitcoin volatility and, if anything, a significant negative relation exists. These results are robust to univariate tests and multivariate tests that use GMM with controls for Newey and West (1987) standard errors. We find further robustness when examining alternative measures of volatility. Similar conclusions are drawn in a number of probit regressions that capture days with extreme changes in the value of Bitcoin. We find that the likelihood of these days occurring is negatively related to the level of speculative trading. These findings suggest that, to the extent that we properly capture speculative trading, such trading is not associated with higher levels of volatility in Bitcoin.

Our study contributes to the literature in three important ways. First, we provide some initial findings about the exchange rate dynamics of Bitcoin. Second, we show that despite the substantial rise in the value of Bitcoin, speculative trading during this period was not unusually high. Third, we demonstrate that the level of speculative trading is not directly associated with the volatility of Bitcoin. The rest of the study follows. Section 2 presents a background on Bitcoin. Section 3 describes the data. In Section 4, we present the results from our empirical tests. Section 5 offers some concluding remarks.

2. The background on bitcoin

As mentioned in the previous section, the objective of this study is to first present some stylized facts about the historic price dynamics of Bitcoin. Second, we test the hypothesis that speculative trading in Bitcoin can explain the presence of the unusually high level of volatility in Bitcoin. In order to further motivate our tests, we discuss the background of Bitcoin. The peer-to-peer electronic monetary system was initially described in a short research paper by Nakamoto (2008), in which the objective of a digital currency is outlined along with how the digital currency could be created and implemented. Nakamoto (2008) discusses the weaknesses of the existing electronic payment system and identifies the high costs of mediating disputes in the existing system. To overcome the inherent trust issues regarding the electronic payment system, Nakamoto (2008) argues that a cryptographic proof would allow, "any two willing parties to transact directly with each other without the need for a trusted third party". The cryptographic proof would provide fraud protection to both sellers and buyers. The intention of the digital currency was to improve of the existing electronic payment system by allowing individuals to exchange electronic coin using digital signatures, which acts as proof of ownership.

The first Bitcoin transactions occurred in January 2009. More than two years later, various reports estimated the circulation of Bitcoin to be more than 6.5 million with about 10,000 users. While the early transactions in Bitcoin appeared to function according to the initial intentions, soon reports began to appear that Bitcoin was being used to purchase illegal drugs. Policy makers around the world became concerned with the anonymity afforded by Bitcoin. In 2013, two U.S. Senate Committee hearings took place. In the committee hearings, testimony about the anonymity of the digital currency brought about additional concerns. Senator Chuck Schumer, for instance, compared Bitcoin to a form online money laundering. Shortly after the congressional testimony, a forum was held in Washington D.C. where additional concerns were raised about the how the anonymity could be used to purchase child pornography. These concerns lead to the creation of a Senate task force that sought out the experts regarding the digital currency, which ultimately found that Bitcoin had yet to replace more traditional ways of funding criminal activity. To date, millions of Bitcoin remain in circulation and, in general, the use of the digital currency remains unregulated in the U.S.

Beyond the potential to fund criminal activity, economists have voiced concerns that, because of the price dynamics, Bitcoin functions more as a speculative asset than as a traditional medium of exchange. Because of its anonymity, Bitcoin may be a target by speculators. Reports have attempted to link the meteoric rise and subsequent collapse in the value of Bitcoin to speculative trading. These reports seem to have merit as the theoretical literature nicely describes the link between speculation and bubbles/crashes in different asset markets. Stein (1987), for example, shows that the presence of speculation can inhibit arbitrage and lead to destabilized asset prices. Shiller (1981) provides some additional insight regarding the link between speculation and the destabilization of prices in equity markets. In particular, Shiller suggests that the observed excess volatility in speculative prices contradicts the efficient markets hypothesis. This link between speculation and volatility provides the framework for our analysis. While our investigation is focused on the idea that speculation might adversely affect Bitcoin as a medium of exchange, examining the informational efficiency of Bitcoin prices may be an important avenue for future research.

3. Data description

We obtain price and volume data from Bitcoin Charts, which provides financial and technical data about the Bitcoin network. Both price and volume data are available on July 17th, 2010. The end of our sample time period is June 1st, 2014. We also gather historical exchange-rate data for 51 other currencies during the same time period from Bloomberg. The purpose in doing so is to provide a simple benchmark when examining Bitcoin volatility.

When measuring speculative trading, we closely follow Llorente et al. (2002) and use a time series model that identifies the dynamic relation between volume and prices. We estimate daily turnover on day t in the following way.[4]

$$\log turn_t = \log(turn_t + 0.00000255) \tag{1}$$

$$vt = \log turn_t - \frac{1}{50} \sum_{s=50}^{-1} \log turn_t \tag{2}$$

v_t is the (50-day) de-trended measure of trading activity.[5] Llorente et al. (2002) then estimates the following time-series equation.

$$R_{t+1} = \beta_0 + \beta_1 R_t + \beta_2 R_t \times v_t + \varepsilon_{t+1} \tag{3}$$

The dependent variable R_{t+1} is the daily return for Bitcoin on day $t + 1$. Llorente et al. (2002) argue that when β_2 is positive, volume is likely to represent speculative trading. Under this circumstance, trading volume directly affects the serial correlation in asset returns. Llorente et al. (2002) also argue that when β_2 is negative, trading volume inversely affects return autocorrelation and can be thought of as hedging activity.

We estimate volatility as the long-run average standard deviation in a GARCH(1,1) model. The model can be written as follows:

$$\sigma_t^2 = \gamma V_L + \alpha m_{t-1}^2 + \beta \sigma_{t-1}^2 \tag{4}$$

We, however, estimate the following version of the model below:

$$\sigma_t^2 = \omega + \alpha \mu_{t-1}^2 + \beta \sigma_{t-1}^2 \tag{5}$$

and obtain estimated parameters for ω, α, and β. Once these parameters are obtained, we can estimate γ, where $\gamma = 1 - \alpha - \beta$. Since $\omega = \gamma V_L$ and we observe σ_t^2, we solve for the long-run variance V_L. Our measure of volatility is the square root of this numeric solution for the long-run variance.

Table 1 provides statistics that describe our sample. Panel A reports the results for Bitcoin while Panel B provides the results for the exchange rates for 51 different currencies. In Panel A, we find that on the average day, the exchange rate (*Bitcoin Rate*) was $123.08, the Bitcoin return (*%ΔBitcoin*) was 0.9%, and volatility (*GARCH(1,1)*) was 5.9%. We define two indicator variables that capture days when the *%ΔBitcoin* is in the 95th percentile (*ExtremeHigh*) and in the 5th percentile (*ExtremeLow*). By construction, the mean of these indicator variables is very close to 5%. We estimate Eq. (3) using 50-day rolling windows so that each day has a measure of speculative trading (*Speculation*). The estimate for β_2 from Eq. (3) is −0.0610, indicating that on the average day, trading activity in Bitcoin is not speculative according to the definition in Llorente et al. (2002). On the average day, trading volume (*Volume*) is more than 53,000, the number of Bitcoins outstanding (*Outstand*) is approximately 9.1 million, and turnover (*Turn*) is the approximately 0.58%.

Figs. 1 and 2 and 2 show some of these summary statistics across time. Fig. 1 shows that while the number of Bitcoins outstanding grew at a relatively constant rate, the value of Bitcoin dramatically increased during the latter portion of our time period. In fact, Bitcoin's value increased to more than $1100 during the end of 2013. In the months that followed, Bitcoin lost nearly 60% of its value. These price dynamics seem to indicate the presence of a bubble in Bitcoin. Coincidently, Fig. 2 shows large spikes in Bitcoin volatility during this period. Contrary to the idea that speculative trading is associated with this increase in volatility and the presence of this bubble, the figure shows that speculative trading was unusually high during this period.[6]

Panel B of Table 1 shows some of the summary statistics for the 51 exchange rates from other currencies. The percent change for the average exchange rate on the average day was 0.01% while volatility was only 3.63%. As before, the indicator variables *ExtremeHigh* and *ExtremeLow* have a mean of approximately 5%.[7]

4. Empirical tests and results

4.1. Univariate correlation

We begin by estimating a correlation matrix for the variables of interest. Table 2 reports the matrix with Pearson Correlation coefficients in the upper-right diagonal and Spearman Correlation coefficients in the lower-left diagonal. A few results are noteworthy. First, speculative trading and Bitcoin returns are unrelated. However, volatility and Bitcoin returns are positively correlated. Interestingly, we do not find that volatility (or the extreme indicator variables) is positively related to speculative trading. If anything, the opposite is true. These results are robust to both Pearson and Spearman coefficients and indicate that speculative trading in Bitcoin does not contribute to Bitcoin returns or its volatility, per se.

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[4] Following prior research (Campbell et al., 1993; Llorente et al., 2002; Covrig and Ng, 2004) we use turnover as the ratio of daily Bitcoin volume and the number of outstanding Bitcoins. We note that we add a small constant (0.00000255) to volume to account for days without trading volume. This constant is further shown to normalize the distribution of trading volume in Llorente et al. (2002) and Covrig and Ng (2004).

[5] Llorente et al. (2002) detrend turnover using *t-200* instead of *t-50*. However, given our data limitations we chose to only use 50days when detrending turnover.

[6] In unreported tests, we examine summary statistics by calendar years and find that while Bitcoin increased from $13 to more than $1100 during 2013, the estimate for speculative trading was lowest among all of the calendar years. Instead, we find positive estimates for speculative trading during the 2010 and 2011 and, to a lesser extent, 2014.

[7] While we would like to measure speculative trading in the other exchange rates, data containing trading volume for these currencies is not publicly available.

Table 1

Summary statistics.

The table reports summary statistics for a variety of different variables. Panel A reports the statistics for the Bitcoin data while Panel B shows some of the summary statistics for average exchange rates for 51 other currencies. Bitcoin is the value of Bitcoin in U.S. dollars. *%ΔBitcoin* is the Bitcoin return or the daily percent change in the value of Bitcoin. *GARCH(1,1)* is the estimate of volatility using GARCH(1,1) model. *ExtremeHigh* is an indicator variable capturing days when the Bitcoin return is in the 95th percentile. *ExtremeLow* is an indicator variable capturing days when the Bitcoin return is in the 5th percentile. *Speculation* is our estimate of speculative trading following Llorente et al. (2002). *Volume* is the daily trading volume in Bitcoin. *Outstand* is the number of Bitcoin outstanding. *Turn* is the daily turnover of the ratio of daily volume scaled by the number of Bitcoin outstanding.

| Panel A. Summary Statistics for the Time Series of Bitcoin Exchange Rates					
	Mean [1]	Median [2]	Standard Dev. [3]	Min [4]	Max [5]
Bitcoin	123.08	11.03	234.74	0.0600	1132.26
%ΔBitcoin	0.0090	0.0020	0.0651	−0.3596	0.4510
GARCH(1,1)	0.0590	0.0432	0.0412	0.0299	0.3265
Extreme High	0.0502	0.0000	0.2183	0.0000	1.0000
Extreme Low	0.0502	0.0000	0.2183	0.0000	1.0000
Speculation	−0.0610	0.0000	0.4188	−1.3380	2.3759
Volume	53,386.08	37,985.76	55,208.58	169.11	668,549.18
Outstand	9,103,445.69	9,502,250.00	2,581,000.45	3,920,050.00	12,838,200.00
Turn	0.0058	0.0043	0.0057	0.0001	0.0606
Panel B. Summary Statistics for Time Series of 51 Country Currencies					
%ΔExRate	0.0001	0.0000	0.0064	−0.0160	0.1658
GARCH(1,1)	0.0363	0.0502	0.0222	0.0003	0.0532
Extreme High	0.0494	0.0000	0.2168	0.0000	1.0000
Extreme Low	0.0494	0.0000	0.2168	0.0000	1.0000
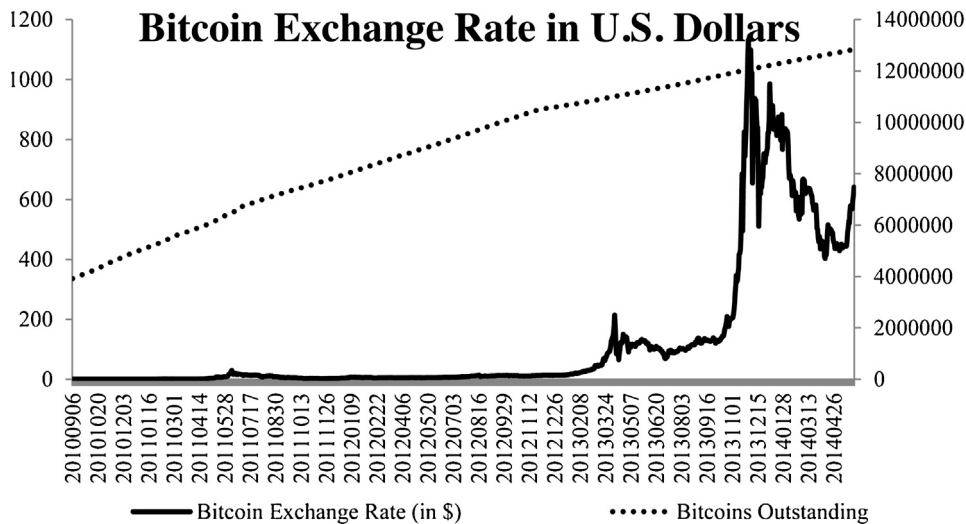
Fig. 1. The figure shows the Bitcoin value and the number of Bitcoins outstanding across our sample time period, which is September 2010 to June 2014.

4.2. Multivariate tests

Next, we provide some more robust multivariate tests. We first estimate the following equation.

$$GARCH(1,1)_t = \beta_0 + \beta_1 Speculation_t + \beta_2 \%\Delta Bitcoin_{t-5,t-1} + \beta_3 Turn_{t-5,t-1} + \beta_4 Ln(Outstand_t) + \beta_5 MktGARCH(1,1)_t + \varepsilon_t \qquad (6)$$

The dependent and independent variables have been defined previously with the exception of *MktGARCH(1,1)*, which is the average volatility estimates of the 51 other exchange rates. We estimate Eq. (6) using GMM and report *p*-values that are obtained from Newey and West (1987) standard errors. Table 3 reports simple regressions in columns [1] through [5] and the full specification in column [6]. The conclusions we are able to draw are similar across columns, so for brevity, we only discuss our findings in column [6]. We find that *Speculation* and *Ln(Outstand)* produce negative estimates while *%ΔBitcoin_{t-5,t-1}* and *Turn_{t-5,t-1}* produce positive coefficients. These results indicate that while past Bitcoin returns and trading activity directly affect volatility, speculative trading does not.

For robustness, we estimate another measure of volatility using the Bitcoin data. In particular, we estimate the 10-day moving average volatility by taking the standard deviation of daily Bitcoin returns from day *t* to *t-10*, where day *t* is the current trading day
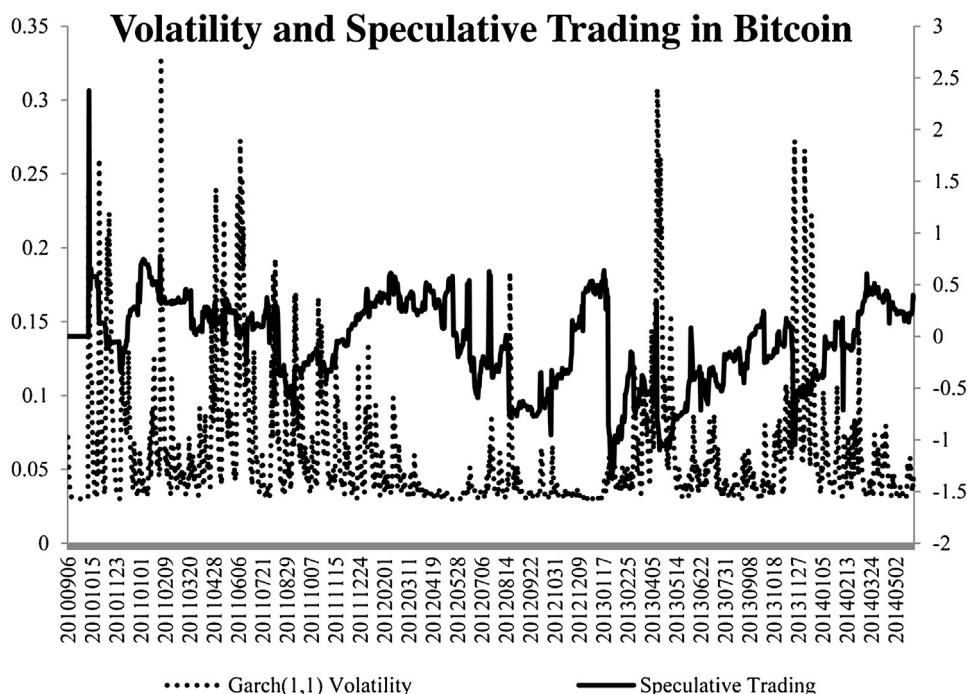
Fig. 2. Estimated Volatility and Speculative Trading in Bitcoin across the Sample Time Period.

Table 2
Correlation matrix.

The table reports the Pearson Correlation Coefficients in the upper-right diagonal and the Spearman Correlation Coefficients in the lower-left diagonal. The variables included in the matrix are our variables measuring speculative trading (*Speculation*), the Bitcoin return (*%ΔBitcoin$_t$*), our estimate for volatility (*GARCH(1,1)*), the two indicator variables *ExtremeHigh* and *ExtremeLow* as well as the volatility estimate for the exchange rates of 51 other currencies (*MktGARCH(1,1)$_t$*). *P*-values reported in parentheses. *,**, *** denote statistical significance at the 0.10, 0.05, and 0.01 levels, respectively.

	Speculation [1]	%ΔBitcoin [2]	GARCH(1,1) [3]	ExtremeHigh [4]	ExtremeLow [5]	Mkt GARCH(1,1) [6]
Speculation	1.0000	0.0209	− 0.1125***	− 0.0210	− 0.0733***	− 0.0010
		(0.442)	(< 0.0001)	(0.440)	(0.007)	(0.972)
%ΔBitcoin	− 0.0220	1.0000	0.1328***	0.6248***	− 0.5294***	0.0116
	(0.418)		(< 0.0001)	(< 0.0001)	(< 0.0001)	(0.671)
GARCH(1,1)	− 0.1017***	0.0890***	1.0000	0.3583***	0.2187***	− 0.0315
	(0.0002)	(0.001)		(< 0.0001)	(< 0.0001)	(0.247)
ExtremeHigh	− 0.0308	0.3781***	0.2642***	1.0000	− 0.0528*	− 0.0036
	(0.257)	(< 0.0001)	(< 0.0001)		(0.052)	(0.896)
ExtremeLow	− 0.0710**	− 0.3781***	0.1919***	− 0.0528*	1.0000	0.0634**
	(0.009)	(< 0.0001)	(< 0.0001)	(0.052)		(0.020)
MktGARCH(1,1)	0.0639**	− 0.0363	0.1152***	0.0030	0.1030***	1.0000
	(0.019)	(0.181)	(< 0.0001)	(0.911)	(0.0001)	

(*10-day MA Volt*). We then re-estimate Eq. (6) using this additional volatility measure as the dependent variable. The results are reported in Table 4. We note that, in unreported tests, w the correlation between the *10-day MA Volt* and *GARCH(1,1)* during our sample time period is 0.75, suggesting that the two estimates of volatility are relatively similar. As before, we report univariate regressions for each of the independent variables in columns [1] through [5]. Column [6] shows the results from the full specification. The inferences that we make between the columns are similar. Therefore, for brevity, we only discuss the full specification. In column [6], we find that past Bitcoin returns and past turnover positively influence the level of Bitcoin volatility. Further, the number of Bitcoins outstanding is negatively related to Bitcoin volatility. After controlling for these variables, the coefficient on *Speculation* is again negative and significant indicating that speculative trading in Bitcoin does not explain the usually high level of volatility.

In our final set of tests, we estimate the following equation using probit regressions.

$$Extreme_t = \beta_0 + \beta_1 Speculation_t + \beta_2 \%\Delta Bitcoin_{t-5,t-1} + \beta_3 Turn_{t-5,t-1} + \beta_4 Ln(Outstand_t) + \beta_5 MktGARCH(1,1)_t + \varepsilon_t \qquad (7)$$

The only difference between Eqs. (7) and (6) is that the dependent variable is now an indicator variable which equals unity on days when percent changes are either in the 95th or 5th percentile (*Extreme*). Furthermore, we include *ExtremeHigh* and *ExtremeLow*

Table 3

Volatility regressions.

The table reports the results from estimating the following equation using GMM.

$GARCH(1,1)_t = \beta_0 + \beta_1 Speculation_t + \beta_2 \%\Delta Bitcoin_{t-5,t-1} + \beta_3 Turn_{t-5,t-1} + \beta_4 Ln(Outstand_t) + \beta_5 MktGARCH(1,1)_t + \varepsilon_t$

The dependent variable is *GARCH(1,1)*, which is our estimate for Bitcoin volatility. The independent variables include our measure of speculative trading (Speculation), the prior five-day Bitcoin return ($\%\Delta Bitcoin_{t-5,t-1}$), the prior five-day volume turnover ($Turn_{t-5,t-1}$), the natural log of outstanding bitcoins ($Ln(Outstand_t)$), and the volatility estimate for the exchange rates of 51 other currencies ($MktGARCH(1,1)_t$). The equation is estimated using GMM and *p*-values, which are obtained from Newey and West (1987) standard errors are reported in parentheses. *,**, *** denote statistical significance at the 0.10, 0.05, and 0.01 levels, respectively.

	[1]	[2]	[3]	[4]	[5]	[6]
Intercept	0.0584***	0.0562***	0.0267***	0.3716***	0.0612***	0.4397***
	(< 0.0001)	(< 0.0001)	(< 0.0001)	(0.0002)	(< 0.0001)	(< 0.0001)
Speculation	−0.0111**					−0.0084***
	(0.032)					(0.009)
%ΔBC Rate$_{t-5,t-1}$		0.3217***				0.2667***
		(0.003)				(0.001)
Turn$_{t-5,t-1}$			0.0535***			0.0541***
			(< 0.0001)			(< 0.0001)
Ln(outstndg)				−0.0196***		−0.0260***
				(0.002)		(< 0.0001)
MktGarch(1,1)					−0.0583	0.0044
					(0.325)	(0.923)
Adj. R2	0.0119	0.0638	0.3228	0.0226	0.0003	0.4080

Table 4

Volatility regressions.

The table reports the results from estimating the following equation using GMM.

$10\text{-}day\ MA\ Volt_t = \beta_0 + \beta_1 Speculation_t + \beta_2 \%\Delta Bitcoin_{t-5,t-1} + \beta_3 Turn_{t-5,t-1} + \beta_4 Ln(Outstand_t) + \beta_5 MktGARCH(1,1)_t + \varepsilon_t$

The dependent variable is the 10-day moving average volatility (*10-day MA Volt*), which is the standard deviation of daily bitcoin returns from day t to t-10, where day t is the current trading day. The independent variables include our measure of speculative trading (Speculation), the prior five-day Bitcoin return ($\%\Delta Bitcoin_{t-5,t-1}$), the prior five-day volume turnover ($Turn_{t-5,t-1}$), the natural log of outstanding bitcoins ($Ln(Outstand_t)$), and the volatility estimate for the exchange rates of 51 other currencies ($MktGARCH(1,1)_t$). The equation is estimated using GMM and *p*-values, which are obtained from Newey and West (1987) standard errors are reported in parentheses. *,**, *** denote statistical significance at the 0.10, 0.05, and 0.01 levels, respectively.

	[1]	[2]	[3]	[4]	[5]	[6]
Intercept	0.0488***	0.0473***	0.0191***	0.4850***	0.0495***	0.5882***
	(< 0.0001)	(< 0.0001)	(< 0.0001)	(< 0.0001)	(< 0.0001)	(< 0.0001)
Speculation	−0.0142***					−0.0148***
	(0.008)					(< 0.0001)
%ΔBC Rate$_{t-5,t-1}$		0.2631***				0.2032***
		(0.001)				(< 0.0001)
Turn$_{t-5,t-1}$			0.0521***			0.0502***
			(< 0.0001)			(< 0.0001)
Ln(outstndg)				−0.0272***		−0.0359***
				(< 0.0001)		(< 0.0001)
MktGarch(1,1)					0.0048	0.0623
					(0.928)	(0.130)
Adj. R²	0.0216	0.0456	0.3059	0.0456	0.0000	0.4132

as additional dependent variables. Table 5 reports the regression results. In each specification, the coefficient on *Speculation* is negative. We note that the coefficient on *Speculation* is not reliably different from zero in column [2]. The marginal probabilities associated with these estimates range from −0.02 to −0.06 suggesting that the estimates for *Speculation* are economically meaningful. The coefficients on the other control variables are similar in sign to those in Tables 3 and 4. Again, these results suggest that volatility in Bitcoin cannot be attributed to speculative trading.

Finding that speculative trading is not driving the presence of excess volatility in Bitcoin is puzzling and suggests that something other than speculation is responsible for the observed bubble in Bitcoin and its volatility. While it would be ideal to continue our tests exploring other possible explanations for volatility, data and information regarding bitcoin is not readily available. For instance, a viable explanation for the observed volatility in Bitcoin might be that a currency lending market does not exist and, therefore, short-sale constraints are binding. The fact that Bitcoin cannot be borrowed and, therefore, cannot be shorted is part of the initial intention of Bitcoin since digital signatures are required as proof of ownership. Perhaps the observed volatility in Bitcoin could be mitigated with the introduction of a currency lending market, or a derivatives market where the currency could be shorted synthetically. A large literature discusses how, in the presence of heterogeneous beliefs, short-sale constraints can contribute to destabilized prices and event bubbles (Miller (1977); Diamond and Verrechia (1987); Hong and Stein, 2003). Admittedly, the lack of data and information about Bitcoin is an important limitation of our study. However, these ideas might be a fruitful avenue for future research.

Table 5

Probit regressions.

The table reports the results from estimating the following equation using traditional probit regressions.

$Extreme_t = \beta_0 + \beta_1 Speculation_t + \beta_2 \%\Delta Bitcoin_{t-5,t-1} + \beta_3 Turn_{t-5,t-1} + \beta_4 Ln(Outstand_t) +$
$\beta_5 MktGARCH(1,1)_t + \varepsilon_t$

The dependent variable is *Extreme* (*ExtremeHigh* or *ExtremeLow*), which are indicator variables equal to unity on days when Bitcoin returns are in the 95th or 5th percentiles. The independent variables include our measure of speculative trading (Speculation), the prior five-day Bitcoin return (%$\Delta Bitcoin_{t-5,t-1}$), the prior five-day volume turnover ($Turn_{t-5,t-1}$), the natural log of outstanding bitcoins ($Ln(Outstand_t)$), and the volatility estimate for the exchange rates of 51 other currencies ($MktGARCH(1,1)_t$). *P*-values are reported in parentheses. *,**, *** denote statistical significance at the 0.10, 0.05, and 0.01 levels, respectively.

	Dependent Variable = Extreme [1]	Dependent Variable = ExtremeHigh [2]	Dependent Variable = ExtremeLow [3]
Intercept	13.4851***	11.7972***	9.1118***
	(< 0.0001)	(0.001)	(0.007)
Speculation	−0.4002***	−0.2403	−0.4242***
	(0.002)	(0.140)	(0.008)
%ΔBC Rate$_{t-5,t-1}$	1.7489	3.7525***	−0.8848
	(0.151)	(0.007)	(0.557)
Turn$_{t-5,t-1}$	0.8322***	0.7100***	0.5516***
	(< 0.0001)	(< 0.0001)	(< 0.0001)
Ln(outstndg)	−0.9785***	−0.8820***	−0.7205***
	(< 0.0001)	(< 0.0001)	(0.001)
MktGarch(1,1)	5.6287**	0.9188	8.2401***
	(0.018)	(0.741)	(0.009)
McFadden R^2	0.1254	0.1193	0.0872

5. Conclusion

Of all of the recent innovations in money markets, few have garnered more attention than the digital currency Bitcoin. Policy makers and regulators are concerned about the negative externalities associated with Bitcoin's anonymity. For instance, during recent congressional testimony, concerns were raised about the possibility that Bitcoin could be used to fund criminal activity. Economists are concerned about the functionality of the digital currency as a medium of exchange. Some economists have argued that Bitcoin acts more like a speculative investment than a currency. Much has been written in the literature about the role that speculation plays in the creation of asset bubbles and the destabilization of prices (Stein, 1987; Shiller, 1981). The objective of this study is to first present some stylized facts about the price dynamics of Bitcoin. Second, we test the hypothesis that speculative trading leads to the unusually high level of volatility in Bitcoin.

Interestingly, we find that the value of Bitcoin, which began trading at only a few cents, climbed as high as $1,132.26 at the end of 2013. In the subsequent months, Bitcoin lost approximately 60% of its value. This unusual rise and fall in the value of an asset seems to appropriately represent the presence of an asset bubble. However, in our tests, we do not find that, during this period, speculative trading was significantly high. Contrary to the idea that speculative trading contributes to Bitcoin's volatility, we do not observe a positive relation in our univariate or multivariate tests. Results from our study should alleviate some concerns about the viability Bitcoin as a currency instead of a speculative investment.

References

Blanchard, O.J., 1979. Speculative bubbles, crashes and rational expectations. Econ. Lett. 3, 387–389.
Bollerslev, T., 1986. Generalized autoregressive conditional hetroskedasticity. J. Econometrics 31, 307–327.
Campbell, J., Grossman, S., Wang, J., 1993. Trading volume and serial correlation in stock returns. Q. J. Econ. 108, 905–939.
Covrig, V., Ng, L., 2004. Volume autocorrelation, information, and investor trading. J. Banking Finance 28, 2155–2174.
Diamond, D.W., Verrechia, R.E., 1987. Constraints of short-Selling and asset price adjustment to private information. J. Financial Econ. 18, 277–311.
Engle, R.F., Kroner, K.F., 1995. Multivariate simultaneous generalized ARCH. Econometric Theory 11, 122–150.
Engle, R.F., 1982. Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation. Econometrica 50, 987–1007.
Flood, R.P., Hodrick, R.J., 1990. On testing for speculative bubbles. J. Econ. Perspect. 4, 85–101.
Hart, O.D., Kreps, D.M., 1986. Price destabilizing speculation. J. Political Econ. 94, 927–952.
Hong, H., Stein, J.C., 2003. Difference of opinion, short-Sales constraints, and market crashes. Rev. Financial Stud. 16, 487–525.
Llorente, G., Michaely, R., Saar, G., Wang, J., 2002. Dynamic volume-Return relation of individual stocks. Rev. Financial Stud. 15, 1005–1047.
Miller, E., 1977. Risk, uncertainty, and divergence of opinion. J. Finance 32, 1151–1168.
Nakamoto, S., 2008. Bitcoin: A Peer-to-Peer Electronic Cash System.
Newey, W.K., West, K.D., 1987. A simple, positive semi-Definite, heteroskedasticity and autocorrelation consistent covariance matrix. Econometrica 55, 703–708.
Scheinkman, J.A., Xiong, W., 2003. Overconfidence and speculative bubbles. J. Political Econ. 111, 1183–1220.
Shiller, R.J., 1981. The use of volatility measures in assessing market efficiency. J. Finance 36, 291–304.
Stein, J., 1987. Informational externalities and welfare-reducing speculation. J. Political Econ. 95, 1123–1145.