Speculative Trading in Bitcoin: A Brazilian Market Evidence

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Abstract

This paper tests the speculative trading in Bitcoin Brazilian market using daily data for Bitcoin spanning the 2011-2018 sample period. Two points are examined: the first is based in stylized facts about price dynamics on Brazilian market and the second implies in testing the hypothesis that speculative trading in Bitcon is resposible for its unusual volatility level. Our results suggest the existence of speculative trading in the Brazilian market based on three different experiments, broadly relevant to both market participants and academic researchers.

Keywords: Bitcoin, Currency Markets, Price Volatility, Asymmetric Information

1. Introduction

Introduced in 2008 by a group of programmers, Bitcoin is a cryptocurrency or virtual money derived from mathematical cryptography (Nakamoto, 2008). An important characteristic of Bitcoin is that code is open and decentralized (Ulrich, 2014); these points, as mentioned by Campos (2015), improve the investor confidence around the world that accepts it as currency for its products. Compared to other traditional financial assets, Bitcoin provides investors a new instrument in portfolio management. Over the last few years, there have been many studies about Bitcoin market. This popularity has attracted the interest of researchers and market practitioners alike, especially searching for a better understanding of the various characteristics of Bitcoin such as styilzed facts (Bariviera, 2017; Cobert et al., 2018; Guesmi et al., 2018), price volatility (Baek and Elbeck, 2015; Dyhrberg, 2016), speculative bubbles (Cheah and Fry, 2015), inneficiency (Nadarajah and Chu, 2017; Bariviera, 2017; Urquhart, 2017; Kristoufek, 2018; Tiwari et al., 2018; Vidal-Tomas and Ibanez, 2018), persistence (Caporale et al., 2018), transaction costs (Dyhrberg et al., 2018), returns (Demir et al., 2018) speculative asset (Baek and Elbeck, 2015; Cheah and Fry, 2015; Baur et al., 2018), price dynamics (Blau, 2018) and informed trading (Feng et al., 2018).

Feng et al. (2018) studied informed trade ahead of cryptocurrency-related events, through a novel indicator. Using a trade-level data of USD/BTC exchange rates, the authors found evidence of informed trading in Bitcoin market prior to large events: quantiles of buyer-initiated orders are abnormally high before large positive events, compared to quantiles of seller-initiated. The profits of informed trading in Bitcoin, could be considered large. Thus, Blau (2018), inquiring about market signals and speculation, provides an exploratory research of Bitcoin's volatility across time, and also tests the relationship between volatility and speculative trading. The author evinces a directly association with speculative trading and Bitcoin's unusual level of volatility.

The volatility of digital currency must be questioned: Are Bitcoin's function currency? Bitcoin has certainly been used as a medium of exchange for many consumers, on the other hand we have the concern that Bitcoin is lrather a speculative investment than a currency. By extending Bitcoin as an investment, which suffers speculation impact, the virtual money reduces its viability as currency. As Blau (2018) affirms approximating speculative trading is a difficult task given that the motives to trade are not observed.

Bitcoin has therefore a place in the financial markets and portfolio management (Dyhrberg, 2016; Kasiampa, 2017), making sure that examining its volatility is crucial. Moreover, the presence of long memory and persistent volatility (Bariviera, 2017) justifies the application of GARCH-type models. The absence of empirical works addressing Bitcoins as a speculative trading in Brazilian market is the reason for this study.

The objective of this study is twofold. First, involves to provide some stylized facts about price dynamics of Bitcoin on Brazilian market. Second, imply in test the hypothesis that speculative trading in Bitcoin is responsible for its unusual level of volatility.

The research contributes to literature in important ways. First, it provides some initial findings about exchange rate dynamics of Bitcoin in Brazilian market. Second, it is demonstrated that the speculative trading level, considering the procedure adopted by Llorente et al. (2002), followed by a univariate and multivariate analysis, frequently occurs on Bitcoin Brazilian market in the current period; where volatility presents a different behavior if compared to returns, which can be affected by the asymmetric information event on the market.

The remainder of this article is organized as follows: Section 2 outlines the Bitcoin and speculative trading background, Section 3 introduces the data and methodology, whilst the speculative trading hipothesis is tested in Section 4. Finally, Section 5 concludes the study.

2. Background on Bitcoin and Speculative Trading

As previously detailed, it is necessary to present some stylized facts about the historic price dynamics of Bitcoin and to analyze causality between Bitcoin's volatility and speculative trading. In order to further motivate our research, we discuss the background of Bitcoin and speculative trading.

Academic interests in anonymous communication researches date back to the early 1980s, and first digital currency, DigitalCash, was launched in 1990 which offered anonymity through cryptographic protocols. The peer-to-peer electronic monetary system was initially described by Nakamoto (2008) with the objective to explain how the digital currency could be created and implanted. In a short paper, Nakamoto (2008) discusses the weaknesses of the existing electronic payment system and identifies the high costs of mediating disputes over the system. To overcome the trust issues regarding the electronic payment system, Nakamoto (2008) argues that it is needed an electronic payment system based on cryptographic proof instead of trust, allowing any two willing parties to transact directly with each other without the need of a trusted third party.

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 10000 users (Blau, 2018). While the first transactions in Bitcoin appeared to function according to the initial intentions, soon reports on Bitcoin being used to purchase illegal drugs began to appear. Policy makers around the world became concerned with the anonymity afforded by Bitcoin. Beyond the potential to fund criminal activity, some researchers have voiced concerns that, because of the price dynamics, Bitcoin functions more as a speculative asset than as a medium of exchange. Considering its anonymity, Bitcoin may be a target for speculators. Stein (1987) and Shiller (1981), for example, have attempted to link the rise and subsequent collapse in the value of Bitcoin through speculative trading.

Today, this has manifested itself into a growing cryptocurrency community which now includes banks, hedge funds and even government. The most popular cryptocurrency, which has the biggest mark capitalization, is Bitcoin. A $1000 USD investment in Bitcoin in July 2010 would have returned $81000000 just seven years later (Phillip et al., 2018). Bitcoin is generally treated as speculative asset (Baek and Elbeck, 2015; Cheah and Fry, 2015; Baur et al., 2018). Thus, some evidences suggest that the cryptocurrency market is still inefficient (Nadarajah and Chu, 2017; Bariviera, 2017; Urquhart, 2017; Kristoufek, 2018; Tiwari et al., 2018; Vidal-Tomas and Ibanez, 2018), with properties such as volatility (Urquhart, 2017), informed trading (Feng et al., 2018) and price dynamics (Baek and Elbeck, 2015; Dyhrberg, 2016; Blau, 2018).

Some reports have foccused to link the meteoric rise and subsequent collapse in Bitcoin's value to speculative trading. This seems to have merit as the theoretical literature nicely describes the link between speculation and bublles in different asset markets (the most popular, stock market). For example, Stein (1987) shows that the presence of speculation can inhibit arbitrage and lead destabilized asset prices. Thus, Shiller (1981) gives some additional insight, showing the link between speculation and destabilization of prices in equity markets; the author suggests that the observed excess volatility in speculative prices contradicts the efficient market hipothesys, associated to low assymetric information degrees. Motivating idea of this paper is that as a network the flow of contracts and negotiations (speculative trading) is key determinant for Bitcoin's price behavior.

Cheah and Fry (2015) test for evidence of speculative bubbles in Bitcoin returns. The authors find that, as other asset classes, Bitcoin prices are prone to speculative bubbles, and the bubble component contained within Bitcoin prices is substantial.

In a more recent study, Cobert et al. (2018) analysem through time and frequency domain, the relationships between three popular cryptocurrencies and a variety of other financial assets, with concluding results that support the view that cryptocurrencies may offer diversification benefits for investors with short investment horizons.

Blau (2018) tests the volatility of Bitcoin and speculative activity showing the debate behind cryptocurencies be a speculative investment asset or currency. Yet about informed trading, Feng et al. (2018) concludes that evidence of informed trading in the Bitcoin market suggests that people who get information before being widely available, profit on their private information - evidencing Bitcoin as a speculative investment asset.

Baek and Elbeck (2015) find evidence to suggest that Bitcoin returns are driven by buyers and sellers internally, and not by fundamental economic factors. Using de-trended ratios, the authors determine Bitcoin returns to be 26 times more volatile than those of the SP 500 index, suggesting that Bitcoin is a speculative investment. The authors however, determine that this classification may change as usage grows, volatility decreases and Bitcoin attracts market and economic influence.

In doing so, Bitcoin may become a more balanced investment, driven both internally and externally. Finally, Kasiampa (2017) explores the ability of several competing GARCH-type models to explain the Bitcoin price volatility, and finds that Bitcoin is different from any other asset on the financial market and thereby creates new possibilities for stakeholders with regards to risk management, portfolio analysis and consumer sentment analysis.

Many legal and normative aspects regarding Bitcoin are still being discussed, pointing differences between countries. For example, the fact that Bitcoin transactions network is decentralized and unregulated (that is, operates without a central authority) to be an asset independent of economic policy (which, if continues to grow, may become an impact assest on the macroeconomic development of a country).

A discussion note edited by IMF (2016) compares currency characteristics, showing the Bitcoin absence of intrinsic value, claim for issuers and legal tender. On the other hand, Bitcoin supply structure is descentralized, with private source, inflexible supply quantity and presents a high cost of production (eletricity consumption of computation). Finally, around macro financial stability risks, Bitcoin presents a high risk of long term hyperdeflation, and do not presents a base money quantity changes to temporary shocks.

Another important point around Bitcoin is the taxation. As mentioned by Campos (2015), the sistematization is important to avoid question around fiscal evasion and gives a more precious notion to state the investment of citizen. This area is still nebulose. For example, in USA, as mentioned by Campos (2015), it serves as a medium of exchange and property. In Canada, Bitcoin is considered a property; while in Germany, Bitcoin is classified as private currency.

The academic literature on digital currencies, such as Bitcoin, has only begun to emerge and is dwarfed by a multitude of popular articles, as mentioned before. So, it is possible to conclude that there are still many uncertainties about Bitcoin in terms of efficiency, market bubbles existence, speculative transactions and currency functions. As already mentioned, against the absence of researches dealing with Bitcoin speculative transactions in the Brazilian market, this theme became the motivation for this study.

3. Data and Methodology

The data was collected from www.bitcoincharts.com which provides complete history of Bitcoin exchanges denoted in various exchanges. The data consists of daily closing prices of Brazilian operators (FoxBit, LocalBitcoin, Mercado Bitcoin, Bitcoin to You, Brasil Bitcoin Market) from August 1st, 2011 to February 28th, 2018 therefore capturing almost seven 7 years of Bitcoins prices.

The results are computed for the usual daily logharithmic return:

$$r_t = (lnP_t - lnP_{t-1}) * 100 \tag{1}$$

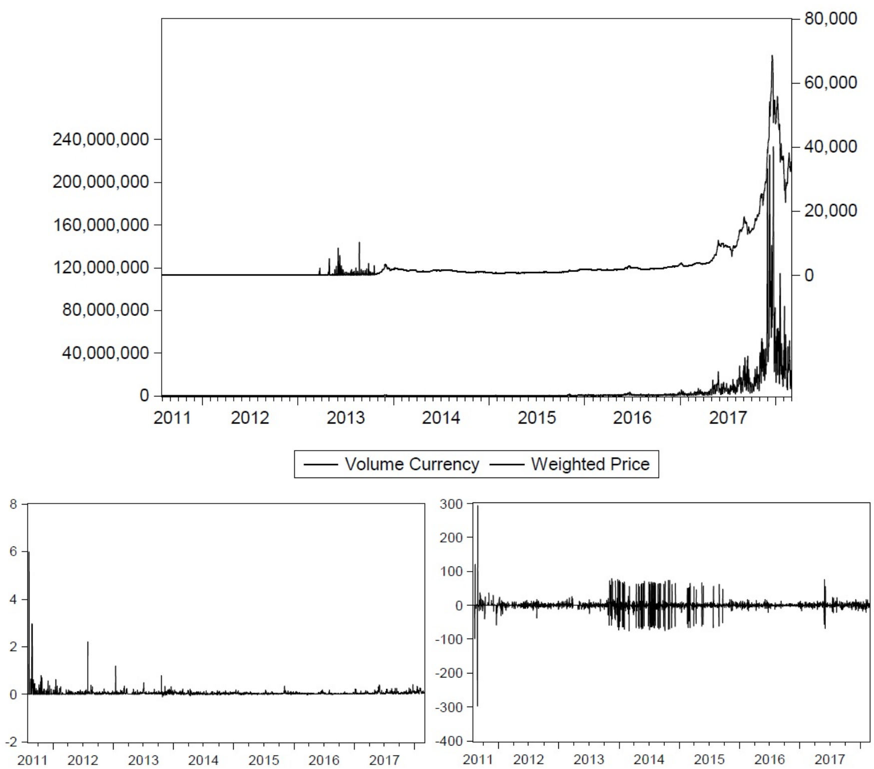
and the daily price volatility, definined as the logharithmic difference between intraday highest and lowest price:

$$ReturnVolatility = lnP_t^{high} - lnP_t^{low} \tag{2}$$

A plot of the data is shown in Figure (1), which detailed: BTC/BRL volume currency and weighted price, BTC/BRL daily returns and BTC/BRL daily returns volatility. We clearly notice that the long bull market lasted almost one year before it ended in July 2017 - July and August are the months during which a major structural in Bitcoin prices is captured.

Figure 1: **BTC/BRL: (i) volume currency and weighted price, (ii) daily returns, and (iii) daily returns volatility**

Note: Figure reports some important time series: volume currency concerns daily trading volume in Bitcoin into Brazilian market; weighted prices is the ratio of volume currency and volume Bitcoin; daily returns is the Bitcoin log return solved by (1) and daily returns volatility is the estimate of volatiliy as detailed in (2)



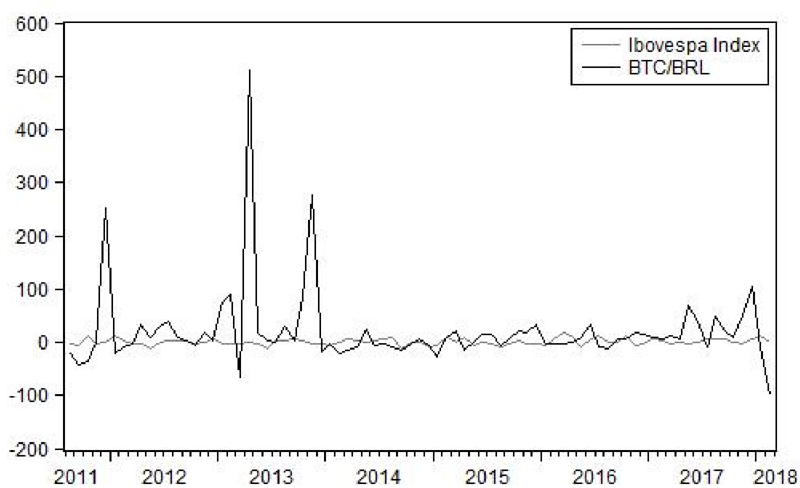
If compared to USA bull market (Balcilara et al., 2017), it is noticed that lenght Brazilian's bull is $\frac{1}{3}$ USA's bull. This phenomenon may have several explanations. The high degree of speculative trading, guided in the context of information asymmetry in the Brazilian market, may lead to greater price sensitivity. This way, Brazil will have a lower peak of high prices, followed by sudden fluctuations, which will not be accompanied by asset price returns - since these are market failures and speculations, not real oscillations of the investment in question.

Yet, being the Bitcoin an asset recently launched around the world, several issues can be pointed out which may incur a greater historical volatility. For example: (i) Around decentralized systems, there is no central party (as a central bank) administering the system or issuing virtual currencies; (ii) Virtual currencies can be obtained in a variety of ways; (iii) Blockchain-based smart contracts are still at an stage, with many unsolved problems; where the unsolved technical difficulties include reliable and integrating external events. In general, the questions listed here, are likely to cause a high degree of asymmetric information and uncertainty between the transactions established in Bitcoin market.

Through the analysis of Figure 1 and Figure 2, it is possible to verify that Bitcoin's price (on Brazilian market) have been extremely volatility over the past several years, and more volatile than the reference index of the Brazilian stock exchange (Ibovespa).

Figure 2: **Volatiliy of Bitcoin and Ibovespa Index**

Note: Figure reports the monthly percent change in the value of Ibovespa Index (%ΔIbovespa) and the monthly percent change in the value of BTC/BRL (%ΔIbovespa)



Aiming to measure speculative trading, we follow Blau (2018) and Llorente et al. (2002) and use a time series model that identifies the dynamic relation between volume and prices. It was employed daily returns and trading volume to analyze the impact of information asymmetry on the dynamic volume-return relation. The estimated daily turnover on day t was based in the following equations:[1]

$$logturn_t = log(turn_t + 0.000025) \tag{3}$$

$$vt = logturn_t - \frac{1}{50}\sum_{s=50}^{-1} logturn_t \tag{4}$$

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

$$R_{t+1} = \beta_0 + \beta_1 R_t + \beta_2 R_t x v_t + \epsilon_{t+1} \tag{5}$$

The dependent variable R_{t+1} is the daily returns for Bitcoin a day $t+1$. Since our volume measure is the abnormal volume (volume in excess of moving average), the β_1 gives the unconditional return autocorrelation. More importantly, the objective in this research is to analyze the link between volume return and investors trading motives; thus, our empirical test focuses on β_2. 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. When β_2 is negative, trading volume inversely affects return autocorrelation and can be thought of as hedging activity. Moreover, the relation between β_2 and the significance of speculative trade relative to hedging trade is monotonic.

4. Results

Through the estimation of Equation (4), using 25-day, 50-day and 100-day rolling windows, each day has a measure of speculative trading (*Speculation*). The original test was using 50-day rolling window. On a second moment, as a robustness test, the Equation (4) was re-estimated with 25-day and 100-day roling windows. The estimate for β_2 from equation (5) is 0.8681, 0.5659 and 0.2790 for 25-day, 50-day and 100-day rolling windows respectively, indicating that on the average day, trading activity in Bitcoin is speculative according to the definition in Llorente et al. (2002). There is the first statement about Bitcoin as a speculative investment for the Brazilian market.

[1] Following prior research (Llorente et al., 2002) 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 (fact that occurs consistently between the years 2011 and 2014). This constant is further shown to normalize the distribution of trading volume in Llorente et al. (2002) and Blau (2018).

Table 1: **Speculative Trading Test**

*,**, *** denote statistical significance at the 0.10, 0.05, and 0.01 levels, respectively

	25-day	**50-day**	**100-day**
β_1	-0.390459***	-0.343292***	-0.364056***
β_2	0.868146*	0.565900*	0.272902*

Table 2 presents the descriptive statistics for Bitcoin returns, volatility, traded volume and speculation. It is possible to observe that volume (*Volume Currency*) is more volatile than returns (*Return*) in the Brazilian Bitcoin market. On the average day, trading volume (*Volume Currency*) is more than 3,000,000, and turn (*Log Turn*) is approximately 2.6527%. The percent change for the average exchange rate on the average day (%Δ*Bitcoin*) is -1.12% while volatility (*Volatility*) is 0.0575%.

Table 2: **Summary Statistics**

The table reports summary statistics for a variety of different variables. Table reports the statistics for the Bitcoin: *Bitcoin* is the value of Bitcoin in R$. %$\Delta$*Bitcoin* is the daily percent change in the value of Bitcoin. *Volume Bitcoin* it the daily value on Bitcoin's contracts negotiated. *Volume Curreny* is the daily value on Bitcoins's on monetary terms (here, R$). Volatility is the daily return volatility in Bitcoin's Brazilian Market. Return is the daily return in Bitcoin's Brazilian Market.

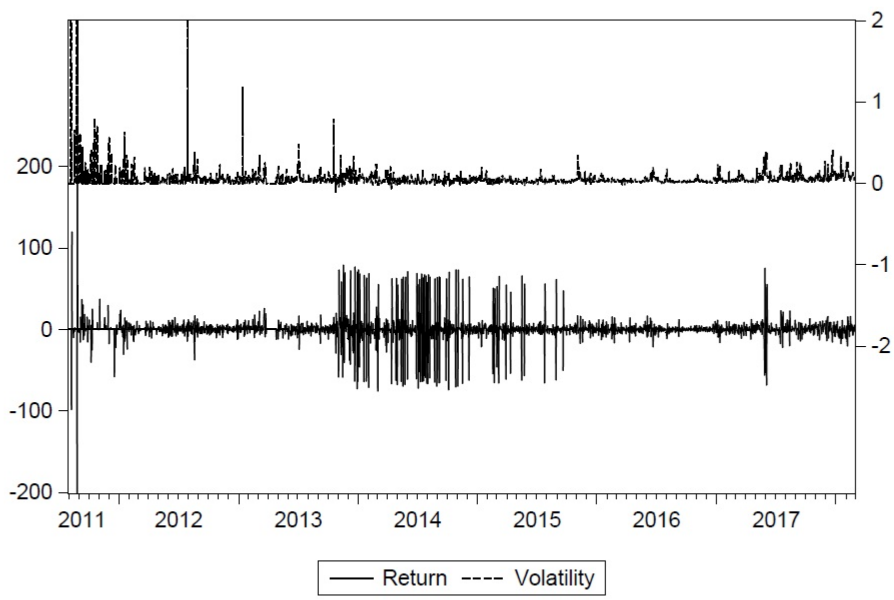
	Bitcoin	**%ΔBitcoin**	**Volume Bitcoin**	**Volume Currency**	**Volatility**	**Return**
Mean	3,777.44	-1.12	289.09	3,589,526.00	0.0575	0.3351
Median	1,057.95	-0.05	134.54	133,587.20	0.0336	0.0000
Maximum	68,610.76	81.94	5,401.37	2,330,000,000.00	5.9914	294.2859
Minimum	0.00	-86.29	0.00	0.00	-0.1024	-296.7330
Std. Dev.	9097.38	6.54	428.53	14,764,957.00	0.1727	17.3129
Skewness	4.04	-0.03	3.74	8.30	22.2259	0.01785
Kurtosis	20.53	0.64	26.71	94.40	658.3414	80.6928
Jarque-Bera	37,357	3,801	61,944	864,559	43,216,737	604,624
Probability	0.00	0.00	0.00	0.00	0.0000	0.0000

If we observe the results about volatility (*Volatility*) and the daily price variation of Bitcoin (%Δ*Bitcoin*), it is possible, again, to suppose the intensity of information asymmetry, since the price of Bitcoin in the Brazilian market fluctuates considerably. Even with a high peak in trading volume and appreciation in 2017, it has daily and negative price variation. That is, investors are led to buy and sell assets, guided by market trends, forming the speculative trading movement, so making the price of the asset fluctuate more than necessary.

Faced with this initial estimate, around the conclusion that on the average day, trading activity in Bitcoin is speculative according to the definition in Llorente et al. (2002), we give suport to efficient market hypothesis on strong evidence. This conclusion concerns that prices reflect instantly even hidden or privileged information. On the other hand, the long term behavior of returns and volatility are different. This kind of behavior could hide some complex underlying dynamics, which exceeds the aim of this analysis up to this moment.

This conclusion becomes evident when we analyze on a more specific scale the behavior of daily return volatility (*Volatility*) and daily return (*Return*): is possible to observe that in bull period the returns do not follow the behavior of volatility. Yet, in several moments the trajectories are divergent, reflecting the high degree of speculation of the market; as show in Figure 3.

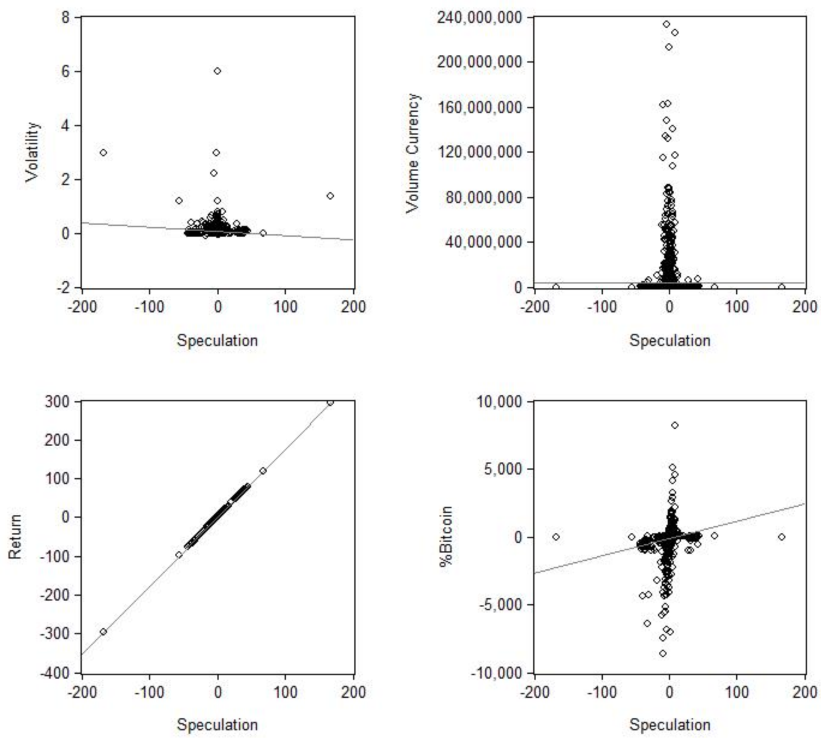
Figure 3: **BTC/BRL: Daily Return x Daily Return Volatility**



Therefore, when anlyzing the relationship between speculative trading and other variables, as shown in Figure (4), it is possible to confirm the hypothesis around the assymetric information. *Speculation* has a perfect correlation with *Return*, for obviously second Equation 5. Thus, speculative trading does not respond positively or negatively to daily return volatility (*Volatility*) , with exception for some extreme cases (we can imagine they are news events). Even more, *Speculation* is indifferent to the daily monetary value in circulation (*Volume Currency*), since it does not present variations when it occurs in bigger oscilations. Lastly, speculative trading responds in a way aligned to the daily variations in Bitcoin's price in Brazilian market (*Bitcoin*), when these have a high variance; that is, when there are significant increases or reductions.

Figure 4: **Speculative Trading Behavior**

The graphics reports summary behavior for a variety of different variables. Figures reports the relation for speculative trading (*Speculation*) comparing to the daily percent change in the value of Bitcoin (*Bitcoin*), the daily return volatility on Bitcoin's Brazilian Market (*Volatility*), the daily return on Bitcoin's Brazilian Market (*Return*) and the daily value on Bitcoin in monetary terms, here R$, (*Volume Curreny*).



Interestingly, Blau (2018) did not find that volatility (or the extreme indicator variables) is positively related to speculative trading. This way, a similarity between USA Bitcoin market and Brazilian Bitcoin market can be observed. Since the speculative transactions are not directly related to Bitcoin's volume traded and only have relation to the Bitcoin's price in extreme cases, we can affirm that there is information asymmetry and uncertainty in the market since there is no logic between the quantity of money used and the quantity of transactions.

More clearly, when it is cited a market where there is no uncertainty and information is evenly distributed to the participants: in case of an increase in Bitcoin's traded volume, speculation must also increase within a normal market dynamics. Yet, if there is a fluctuation in the price of money, speculative transactions should accompany such fluctuations. However, in general, this movement was not being observed. Thus, it can be concluded that the market may have flaws, regarding asymmetric information and degrees of uncertainty that compromise investor confidence.

4.1. *Univariate Correlation*

After obtaining the returns, the information of return fluctuation (volatility series) over time can be estimated by fitting GARCH(1,1) to the returns. The volatility was estimated as the long-run average standard deviation in a GARCH(1,1) model. The model can be written as follows: where γ, α and β are the weight assigned to long-run average rate V_t returns squared and variance. The weights γ, α and β must sum to unity, that is: $\gamma + \alpha + \beta = 1$.

$$\sigma_t^2 = \gamma V_t + \alpha m_{t-1}^2 + \beta \sigma_{t-1}^2 \tag{6}$$

As Blau (2018), we estimate the following version of the model below, where $\omega > 0$, $\alpha \geq 0$ and ≥ 0. In order to guarantee the variance to be positive, was set $\alpha + \beta < 1$. The equation is often used for the purpose of estimating volatility.

$$\sigma_t^2 = \omega + \alpha \mu_{t-1}^2 + \beta \sigma_{t-1}^2 \tag{7}$$

and obtain estimated parameters for ω, α and β. Once these parameters are obtaining, it can be estimated γ, where $\gamma = 1 - \alpha - \beta$. Since $\omega = \gamma V_l$ and 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 3 reports the matrix of Correlation Coefficients. A few results are noteworthy. First, speculative trading (*Speculation*) and Bitcoin returns volatility (*GARCH(1,1)*) are positively related. Interestingly, it is found that volatility (*GARCH(1,1)*) is positively related to speculative trading (*Speculation*), which confirms our proposition around Bitcoin and an opportunity of speculative investment. Let us emphasize here that this is the second statement on Bitcoin as a speculative investment for the Brazilian market.

Table 3: Correlation Matrix

Note: This table reports the Correlation Coefficients. The variables included in the matrix are our variables about speculative trading (*Speculation*), the Bitcoin daily return (%Δ *Bitcoin*), our estimate for volatility (*GARCH(1,1)*), indicator variables *High* and *Low*.

	Speculation	**%Δ Bitcoin**	**GARCH(1,1)**	**Volume Currency**	**Low**	**High**
Speculation	1	0.1906	0.0885	-0.0008	0.0039	0.0017
%Δ Bitcoin	0.1906	1	0.0465	-0.2793	-0.3097	-0.3267
GARCH(1,1)	0.0885	0.0465	1	-0.0883	-0.0490	-0.0585
Volume Currency	-0.0008	-0.2793	-0.0883	1	0.7864	0.8180
Low	0.0039	-0.3097	-0.0490	0.78644	1	0.9974
High	0.0017	-0.3267	-0.0585	0.8180	0.9974	1

4.2. *Multivariate Test*

Next, it is provided a robust multivariate test, estimating the following equation, as used in Blau (2018). The dependent variable have been defined previously, when we estimated volatility as the long-run average standard deviation in a GARCH(1,1) model. The independent variables used: Speculation, %ΔBitcoin, Volume Currency, were analyzed on Summary Statistics.

$$GARCH(1,1) = \beta_0 + \beta_1 Speculation_t + \beta_2 \%\Delta Bitcoin_{t-5,t-1} + \beta_3 VolumeCurrency + \epsilon_t \quad (8)$$

Equation (8) was estimated using GMM and report p-values that are obtained form Newey and West standad errors. Table 4 reports simple regressions in colums. Among the findings, are those the daily percent change in the value of Bitcoin (*%ΔBitcoin*) has a positive impact on volatility (*GARCH(1,1)*), but it is not statistically significant. Thus, daily value on Bitcoin (*Volume Currency*) produces negative estimates while speculative trading (*Speculation*) produces positive coefficients. These results indicate that while daily value of Bitcoin in monetary terms does not directly affect volatility, speculative trading does. Here it is expressed here the third affirmation about Bitcoin as a speculative investment for the Brazilian market.

Table 4: Volatility Regressions: GARCH(1,1)

Note: The table reports the results from estimating the following equation using GMM.
$GARCH(1,1) = \beta_0 + \beta_1 Speculation_t + \beta_2 \%\Delta Bitcoin_{t-5,t-1} + \beta_3 VolumeCurrency + \epsilon_t$
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 (*%ΔBitcoin*), the daily value of Bitcoin's on monetary terms (*Volume Currency*). The equation is estimated using GMM and p-values, which obtained from Newey and West standard errors are reported in parentheses. *,**,*** denote statistical significance at the 0.10, 0.05, 0.01 levels, respectively.

Intercept	**Speculation**	*%ΔBitcoin*	**Volume Currency**	R^2
-0.0053 ***	0.0001 *	0.0014	-0.0001 ***	0.1566
(0.0005)	(0.0001)	(0.0000)	(0.0000)	

As a robusteness test, another measure of volatility using the Bitcoin data was estimated, most specifically the Volatility series. So, the estimation supports a 5-day moving average volatility by taking the standard deviation of daily Bitcoin returns (Return) from day t to day t-5, where day t means the current trading day (5-day Volatility). Then, it was re-estimated Equation 8, changing the dependent variable:

$$5 - dayVolatility = \beta_0 + \beta_1 Speculation_t + \beta_2 \%\Delta Bitcoin_{t-5,t-1} + \beta_3 VolumeCurrency + \epsilon_t \quad (9)$$

The results, repported in Table 5 suggest that the daily percent change in the value of Bitcoin (%ΔBitcoin) has a negative impact on volatility (5-day Volatility). Once again, speculative trading (Speculative) produces positive and statistically significant coefficients. As expressed in Blau (2018), we note that the correlation between 5-day Volatility and GARCH(1,1) is 0.51, suggesting that both estimates of volatility are relatively similar.

Table 5: Volatility Regressions: 5-day Volatility

Note: The table reports the results from estimating the following equation using GMM.
$5 - dayVolatility = \beta_0 + \beta_1 Speculation_t + \beta_2 \%\Delta Bitcoin_{t-5,t-1} + \beta_3 VolumeCurrency + \epsilon_t$
The dependent variable is 5-day Volatility, which is our estimate for Bitcoin volatility. The independent variables include our measure of speculative trading (*Speculation*), the prior five-day Bitcoin return (*%ΔBitcoin*), the daily value on Bitcoin's on monetary terms (*Volume Currency*). The equation is estimated using GMM and p-values, which are obtained from Newey and West standard errors reported in parentheses. *,**,*** denote statistical significance at the 0.10, 0.05, 0.01 levels, respectively.

Intercept	**Speculation**	*%ΔBitcoin*	**Volume Currency**	R^2
0.2327	0.0003 ***	-0.0004 ***	0.0000 **	0.1295
(0.0000)	(0.0008)	(0.0009)	(0.0000)	

Finding that speculative trading is driving the presence of excess volatility in Bitcoin into Brazilian market suggests that assymetric information and uncertainty could be responsible for the observed bubble in Bitcoin and its volatility. For instance, a justification for the expressed results may lie in the fact that Brazil is a developing market, with a less developed market of assets compared to countries like the United States [2], and with a high degree of uncertainty for investment due to the economic instability situation which affects the country. Perhaps, the observed volatility in Bitcoin could be mitigated with the introduction of a currency lending market, a viable smart contract systems and an effective regulation of virtual currencies poses and consumer protection.

5. Conclusion

The objective of this paper was to provide facts that detailed the price dynamics of Bitcoin in Brazilian market and test the hypothesis that speculative trading in Bitcoinis is present and responsible for unusual level of volatility on Bitcoin's price.

Although a large amount of literature has focused on the role of traded volume in predicting movement in stock returns and volatility and inefficiency of Bitcoin into USA market, the predictability of speculative trading for the returns and volatility in the Bitcoin market remains little

[2] Blau (2018) found 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.

explored in a general context, and unexplored into Brazilian market. To address this literature gap, it was examined daily data covering the period of 1st August 2011 to 28th February 2018, which interestingly show that Bitcoin returns, volatility and volume do not follow the same trajectory. Methodologically, besides providing an exploratory analysis of value and volatility of the Bitcoin on Brazilian market across time, was employed a speculative trading test based on Llorente et al. (2002) and explore a univariate and multivariate tests to give support to the results found.

Our results are summarized as follows: First, the Bitcoin's bull on Brazilian market presented a short duration, given the volatility exposed into period; showing signs of asymmetry in market information and uncertainty. Second, it was observed the different trajectories between volatility and return, reflecting the high degree of speculation of the market. Third, it was proved the existence of speculative trading in Bitcoin's Brazilian market through three different experiments: (i) The estimated β_2 from Llorente et al. (2002) equation is positive, indicating that on the average day, trading activity in Bitcoin is speculative; (ii).A positive correlation between volatility (here represented by a model GARCH(1,1)) and speculation was found confirming, confirming our proposition around Bitcoin as an opportunity of speculative investment for Brazilian market; (iii) Providing regressions with two tipes of volatility, we conclude that speculative trading produces a positive relationship with volatility.

The evidence of speculative trading in the Bitcoin Brazilian market suggests that people who get information before it is widely available, profit on their private information. This study is relevant for global regulators who supervises cryptocurrency markets, macroeconomists, financial economists and asset managers, and such understanding has motivated several studies and theoretical advances in the modelling of the Bitcoin volatlility and specific features.

References

Baek, C. and Elbeck, M. (2015). Bitcoins as an investment or speculative vehicle? a first look. *Applied Economics Letters*, 22(1), 30-34.

Balcilara, M., Bourid, E., Guptac, R., and Roubaudb, D. (2017). Can volume predict bitcoin returns and volatility? a quantiles-based approach. *Economic Modelling*, 64, 74-81.

Bariviera, A. F. (2017). The inefficiency of bitcoin revisited: A dynamic approach. *Economics Letters*, 161, 1-4.

Baur, D. G., Hong, K., and Lee, A. D. (2018). Bitcoin: Medium of exchange or speculative assets? *Journal of International Financial Markets, Institutions e Money*, 54, 177-189.

Blau, B. M. (2018). Price dynamics and speculative trading in bitcoin. *Research in International Business and Finance*, 43, 493-499.

Campos, G. I. R. V. (2015). Bitcoin consequÃªncias jurÃdicas do desenvolvimento da moeda virtual. *Revista Brasileira de Direito*, 11-2.

Caporale, G. M., Gil-Alana, L., and Plastun, A. (2018). Persistence in the cryptocurrency market. *Research in International Business and Finance*, 46, 141-148.

Cheah, E.-T. and Fry, J. (2015). Speculative bubbles in bitcoin markets? an empirical investigation into the fundamental value of bitcoin. *Economics Letters*, 130, 32-36.

Cobert, S., Megan, A., Larkin, C. J., Lucey, B. M., and Yarovaya, L. (2018). Exploring the dynamic relationships between cryptocurrencies and other financial assets. *Economics Letters*, 165, 28-34.

Demir, E., Gozgor, G., Lau, C. K. M., and Vigne, S. A. (2018). Does economic policy uncertainty predict the bitcoin returns? an empirical investigation. *Finance Research Letters*, 26, 145-149.

Dyhrberg, A. H. (2016). Bitcoin, gold and the dollar - a garch volatility analysis. *Financial Research Letters*, 16, 85-92.

Dyhrberg, A. H., Foley, S., and Svec, J. (2018). How investible is bitcoin? analysing the liquidity and transaction costs of bitcoin markets. *Economics Letters*, 171, 140-143.

Feng, W., Wang, Y., and Zhang, Z. (2018). Informed trading in the bitcoin market. *Finance Research Letters*, 26, 63-70.

Guesmi, K., Saadi, S., Abid, I., and Ftiti, Z. (2018). Portfolio diversification with virtual currency: Evidence from bitcoin. *International Review of Financial Analysis*, Forthcoming.

IMF, S. T. (2016). Virtual currencies and beyond: Initial considerations. *Internationl Monetary Fund*, 1.

Kasiampa, P. (2017). Volatility estimation for bitcoin: A comparison of garch models. *Economic Letters*, 158, 3-6.

Kristoufek, L. (2018). On bitcoin markets (in)efficiency and its evolution. *Physica A*, 503(1), 257-262.

Llorente, G., Michaely, R., Saar, G., and Wang, J. (2002). Dynamic volume-return relation of individual stocks. *Review Financial Studies*, 15(4), 1005-1047.

Nadarajah, S. and Chu, J. (2017). On the inefficiency of bitcoin. *Economics Letters*, 150, 6-9.

Nakamoto, S. (2008). Bitcoin: A peer-to-peer eletronic cash system.

Phillip, A., Chan, J. S., and Peiris, S. (2018). A new look at cryptocurrencies. *Economics Letters*, 163, 6-9.

Shiller, R. (1981). The use of volatility measures in assessing market efficiency. *The Journal of Finance*, 159(2), 291-304.

Stein, J. C. (1987). Informational externalities and welfare-reducing speculation. *Journal of Political Economy*, 95(6), 1123-1145.

Tiwari, A. K., Jana, R., Das, D., and Roubaud, D. (2018). Informational efficiency of bitcoinâ"an extension. *Economics Letters*, 163, 106-109.

Ulrich, F. (2014). Bitcoin a moeda digital. *Editora Misses*.

Urquhart, A. (2017). Price clustering in bitcoin. *Economics Letters*, 159, 145-148.

Vidal-Tomas, D. and Ibanez, A. (2018). Semi-strong efficiency of bitcoin. *Finance Research Letters*, Forthcoming.