Analyzing Bitcoin Price Volatility

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Abstract

In this work we do an analysis of Bitcoin's price and volatility. Particularly, we look at Granger-causation relationships among the pairs of time series: Bitcoin price and the S&P 500, Bitcoin price and the VIX, Bitcoin realized volatility and the S&P 500, and Bitcoin realized volatility and the VIX. Additionally, we explored the relationship between Bitcoin weekly price and public enthusiasm for Blockchain, the technology behind Bitcoin, as measured by Google Trends data. we explore the Granger-causality relationships between Bitcoin weekly price and Blockchain Google Trend time series. We conclude that there exists a bidirectional Granger-causality relationship between Bitcoin realized volatility and the VIX at the 5% significance level, that we cannot reject the hypothesis that Bitcoin weekly price do not Granger-causes Blockchain trends and that we cannot reject the hypothesis that Bitcoin realized volatility do not Granger-causes S&P 500.

Acknowledgements

First I want to thank my advisors: Professor Hawkins and Dana Hobson. Their support and advice was fundamental for this work. This work is dedicated to my family: Rosmery, Grocio and Luis. I am blessed with their constant support and love through this long journey. I would also like to thank my family from Mexico, Bolivia and Peru for their support during these last 4 yours.

Contents

1 Introduction

Bitcoin is a digital currency that was created in 2009 by Satoshi Nakamoto and since then it has caught a lot of attention due to its decentralized characteristics and the technology behind it. Bitcoin is a peer-to-peer system where transactions take place without a central player. The transactions are verified by the nodes of the network and recorded in the Blockchain. The Blockchain is a distributed database that keeps a permanent record of what is happening in the network. Since the popularization of Bitcoin, this technology has caught attention of several technology companies who started to do research on the applications and opportunities of this technology. In this paper, we are particularly interested in studying Bitcoin price (BTC) and Bitcoin realized volatility (BTC_Vol) with respect to financial markets measures, like the S&P 500 and the S&P 500 volatility index (VIX), and the market interest on Blockchain technology.

The understanding of Bitcoin volatility is relevant for governments, investors and regulators. With a better understanding of the price and volatility of this cryptocurrency there can be better regulations for its formal use in different economies around the world. The understading of these aspects of Bitcoin could reduce the risk of using and investing with this currency. This way, investors could consider doing bigger investments using Bitcoin or, given the relationship with the S&P 500 and VIX, use it as a proxy of how the market is behaving. Finally, with the relationship between Bitcoin price and Blockchain online queries, investors or government officials interested in the Blockchain technology space could follow the movements of Bitcoin price to have a better sense of how the Blockchain space is developing.

Following some studies previously done, we decided to study the relationship between Bitcoin price and Bitcoin realized volatility with the online searches of Blockchain, the technology behind Bitcoin. Particularly, we are trying to answer the questions: Can the knowledge of the S&P 500 or the VIX data help predict future Bitcoin price or Bitcoin realized volatility and vice versa? Additionally, we are exploring whether Bitcoin price is related to online searches of the word Blockchain. We use the S&P 500 as a comprehensive measure of the behavior of the stock markets and Google Trends data as a good measure of market interest on Blockchain, particularly we use Blockchain Google Trends (BGT).

To measure the level of relationship between our variables of interest, we use a Vector Autoregression (VAR) model. Then, we apply a Granger-causality test to test the joint significance of the results. Saying that time series X Granger-causes time series Y refers to the fact that using past values of X together with past values of Y lead to better prediction than just using past values of Y for the prediction. It is important to note that Granger-causation can be bidirectional. When applying these tests to the time series of interest, we found that there is no Granger-causality relation between Bitcoin price and the S&P 500 and Bitcoin price and the VIX. Furthermore, we found that Bitcoin price realized volatility Granger-causes the S&P 500 at the 5% significant level but we don't have this type of relationship in the other direction. In a similar way, we find that Bitcoin price weekly Granger-causes Blockchain Google Trends (BGT) at the 10% significant level, but find no relationship in the other direction. Finally, we found strong bidirectional Granger-causality relations, at the 5% significant level, between Bitcoin price volatility and the S&P 500 price and Bitcoin price volatility and the VIX.

The literature regarding Bitcoin price and Bitcoin realized volatility focus on determining the main economic factors affecting Bitcoin price and has focused only on a small number of financial variables, the Dow Jones index, the Nikkei 225 and gold, Dyhrberg (2015) and van Wijk (2013). Furthermore, there are several analysis on how online queries of the word "Bitcoin", in Google, Wikipedia or Twitter, affect the price Bitcoin Kristoufek (2013) and Davies (2014). With this work, we want to fill the gap left and focus on the effect of S&P 500 and VIX on Bitcoin price and realized volatility and the relationship between Bitcoin price and realized volatility with market interest on Blockchain.

2 Literature Review

Since Bitcoin is such a recent creation, there has been a slow but steady increase in the amount of research work done in relation to this cryptocurrency. In recent years, there has been more research on the price formation of Bitcoin, the main drivers of Bitcoin price and, to a smaller extent, on the volatility of Bitcoin's price. In the paper "The economics of Bitcoin Price formation", Ciaian et al. (2014) studied the relationship between the price of Bitcoin and the demand and supply fundamentals of this cryptocurrency, some global financial indicators (oil price and the Dow Jones index) and Bitcoin's attractiveness for investors (i.e. the volume of daily Bitcoin views on Wikipedia). The authors studied the impact of each of the variables on Bitcoin's price individually, as well as the interaction of these factors on the price of the cryptocurrency. They conclude that, to a large extent, the price of Bitcoin is determined by the interaction of supply and demand, which are among the key drivers. However, they are not able to reject the hypothesis that speculation and Bitcoin's attractiveness for investors affect Bitcoin price. Finally, the authors do not find evidence that the financial variables have an effect on Bitcoin's price.

The value of Bitcoin and its relationship to different financial data (e.g. the Dow Jones, FTSE 100, Nikkei 225 and the WTI oil) was examined by van Wijk (2013). The authors were able to conclude that the Dow Jones, the WTI oil price and the euro-dollar exchange rate have a significant impact on the price of Bitcoin in the short run but only the Dow Jones has a significant impact on the value of Bitcoin in the long run. Also, the researchers concluded that other variables, like the dollar-yen exchange rate and the Nikkei 225, have no statistically significant effect on the formation of Bitcoin price.

The price returns and volatility changes in Bitcoin market were studied by Bourie et al. (2016). Furthermore, their analysis show a negative relation between the US implied volatility index (VIX) and Bitcoin realized volatility.

Fundamental factors like usage in trade, money supply and price level were found to be important in the determination of Bitcoin price in the long run according to Kristoufek

(2015). Additionally, the author analyzes the effect of Bitcoin popularity, quantifying it with data from Google Trends and Wikipedia searches containing the word Bitcoin, on the cryptocurrency price. He concludes that that the prices of bitcoin are driven by the investor's interest in the crypto-currency. Additionally, the author uses the financial stress index and gold price to make test the claim that Bitcoin is a safe haven. The analysis allowed him to conclude that Bitcoin does not appear to be a safe haven.

The relationship between Bitcoin price and the interest in the currency as measured by online searches in Wikipedia and Google was examined by Kristoufek (2013). The author was able to conclude not only that there exist a strong correlation between price level and the queries in Wikipedia and Google, but also found a strong bidirectional causal relationships between the prices and searched terms.

The relationship between Bitcoin realized volatility and the popularity of the cryptocurrency measured by the queries or tweets in Google or Twitter respectively that contained the word bitcoin was studied by Davies (2014). The author was able to conclude that changes in Google Trends of Bitcoin do have an effect on the volatility of Bitcoin and that changes in Bitcoin volatility also have an effect on Google searches for Bitcoin. Additionally, the author was able to conlcude that Twitter searches do not have an effect on the volatility of Bitcoin but that changes in the volatility of Bitcoin do have an effect in tweets about Bitcoin.

This paper fills the gap left by the works described above by analyzing the influence of the S&P 500 and VIX on Bitcoin's price and volatility. Thus, we want to consider different financial variables that could affect the price of Bitcoin or movements of it. Furthermore, we are also interested in assessing the effect of the popularity of the technology behind Bitcoin, namely the Blockchain, on the price of this cryptocurrency and movements of it.

3 Data and Descriptive Statistics

We use data from the Bitcoin-USD exchange price, the S&P500, the VIX, and data from Google Trends regarding searches that contain the word "Blockchain" (BGT).

We use daily data of Bitcoin price from the 15th of September of 2010 until the 13th of April of 2017 and obtained this data from the exchange CoinDesk BPI. [1] The CoinDesk BPI exchange "represents an average of bitcoin prices across leading global exchanges that meet criteria specified by the XBP" according to CoinDesk, where the global exchanges included are "Bitstamp", "Coinbase", "itBit", "OKCoin","BTC China" and "Huobi". We computed the 1 month realized volatility of the Bitcoin price by calculating the return series of the price data (closing price of day n - closing price of day $n-1$), then computed the standard deviation of 30 days (1 month) and finally annualized by multiplying by a factor of $\sqrt{262}$. In Figure 1 we see plots of Bitcoin price and Bitcoin volatility for the time span chosen.

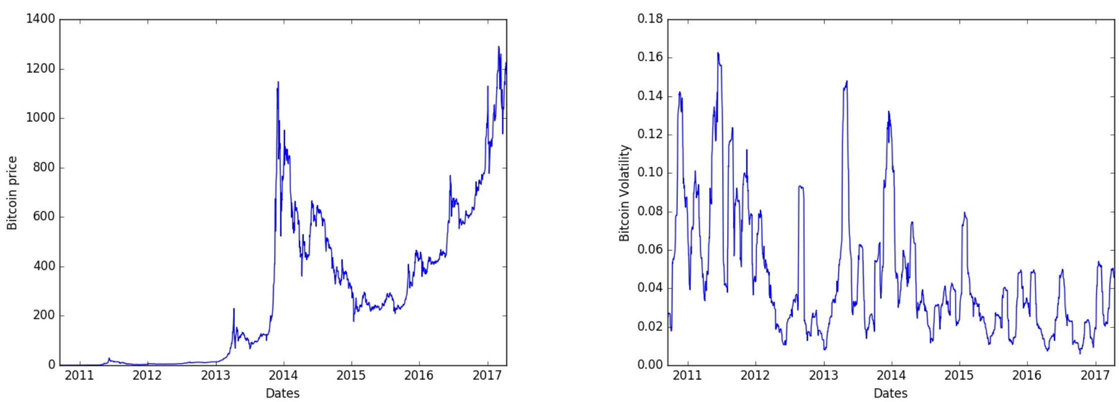

Figure 1: Behavior of Bitcoin price and realized volatility. On the left panel we see the behavior of Bitcoin price (BTC) throughout time and on the right panel we see the behavior of Bitcoin realized volatility (BTC_Vol)

We obtained the daily data for the S&P500 and the VIX from Yahoo! finance [2] for the

[1] http://www.coindesk.com/price/
[2] https://finance.yahoo.com/

same time span as for Bitcoin prices. Furthermore, we see graphs showing the plots of Bitcoin price and volatility with the S&P500 and the VIX respectively. From our calculations, we were able to obtain the following correlations between the time series $\rho_{BTC,S\&P500} = 0.8099$, $\rho_{BTC,VIX} = -0.4278$, $\rho_{BTC_Vol,S\&P500} = -0.4611$ and $\rho_{BTC_Vol,VIX} = 0.3055$. From these correlations, we can clearly see that these variables are strong candidates to have some statistical causation between them. We can see the graphs showing some of the relationship between these variables in Figure 2 and Figure 3:

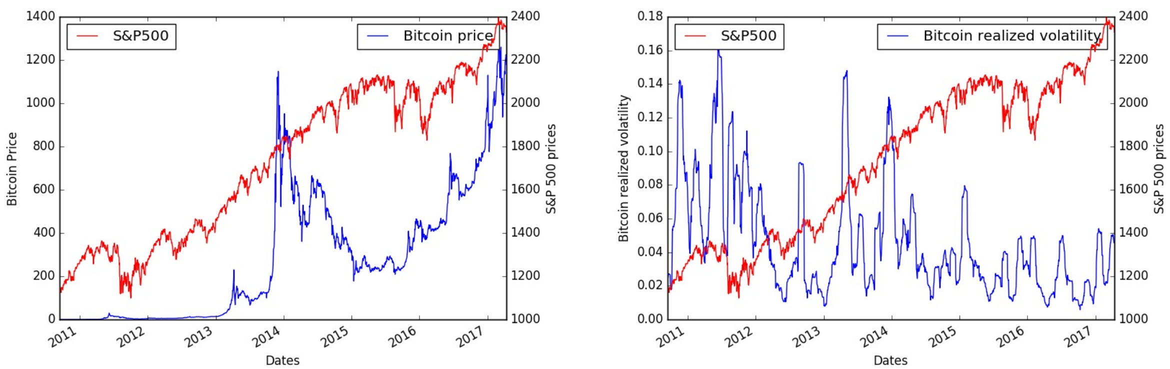

Figure 2: Behavior of BTC and BTC_Vol compared to the S&P500. On the left panel we show a graph with the data of BTC and the S&P500. On the left panel we show a graph with the data of BTC_Vol and the S&P500

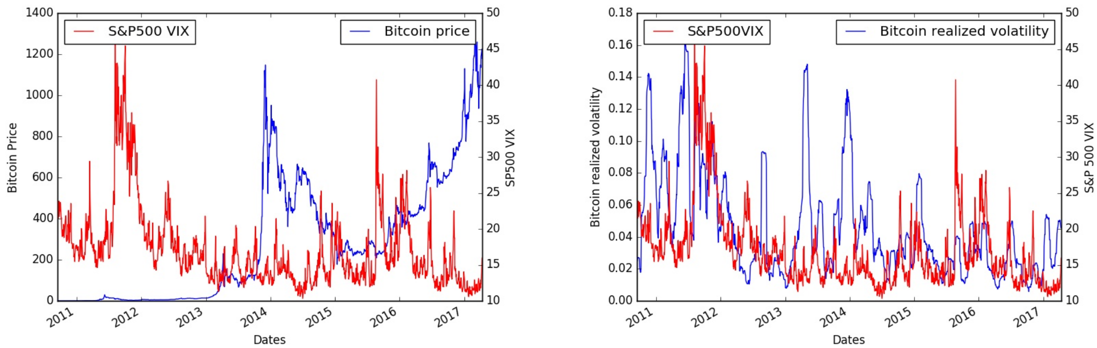

Figure 3: Behavior of BTC and BTC_Vol compared to the VIX. On the left panel we show a graph with the data of BTC and the VIX. On the right panel we show a graph with the data of BTC_Vol and the VIX.

Additionally, we present the data we obtained from Google Trends regarding the queries that included the word "Blockchain" (BGT). First of all, it is important to consider that Google Trends is a search engine that is intended to measure the popularity of a term over time. This tool allows users see how often a term is searched in Google in relation to the total searches. The data you obtain from this kind of software is a normalized series where the highest value of search during the period one is looking at is 100 and every other value is relative to this 100.

In our case, Google Trends gives us weekly data for the popularity of the term "Blockchain" from the 6th of May of 2012 until the 26th of March of 2017. As such, we also subselected our data from Bitcoin price we already had to obtain a weekly data set of the prices. From this data set, we also computed a 4 week realized volatility of the Bitcoin price. With these data sets, we obtained the following correlations: $\rho_{BTC,BGT} = 0.7680$ and $\rho_{BTC\_Vol,BGT} = -0.1964$. From the correlation data, we can discard doing further analysis between Bitcoin volatility and Blockchain Google Trends data due to the low correlation compared to the other correlations we obtain. Now in Figure 4 we observe the relation between Bitcoin price and Blockchain Google Trends.

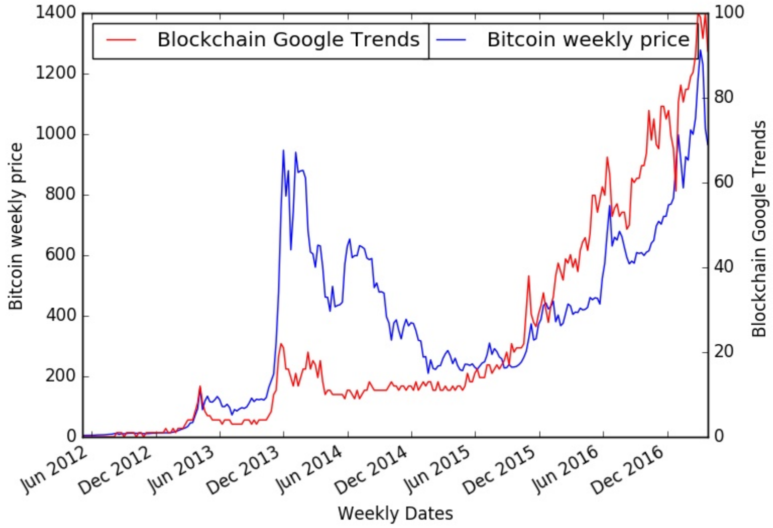

Figure 4: Bitcoin price and Blockchain Google Trends.

Finally, we present summary statistics of the data sets we will be working with.

Table 1: Summary statistics daily data

	BitCoin Price	Bitcoin/USD historical volatility	Close S&P500	S&P 500 VIX Close
count	1657	1657	1657	1657
mean	283.75	0.04	1731.18	17.04
std	302.95	0.03	359.76	5.48
min	0.06	0.00	1099.22	10.32
25%	9.35	0.02	1362.16	13.41
50%	228.65	0.03	1804.76	15.58
75%	456.27	0.05	2063.14	18.66
max	1290.79	0.16	2395.95	48.00

Table 2: Summary statistics weekly data

	Close Bitcoin Price weekly	Bitcoin price 1mVolatility	blockchain
count	256	256	256
mean	367.80	0.65	23.11
std	287.12	0.55	25.34
min	4.93	0.05	0.00
25%	118.54	0.28	4.00
50%	324.04	0.49	12.00
75%	589.82	0.82	34.75
max	1277.68	3.71	100.00

We can see from these Tables 1 and 2 that there is a lot of variation among the data as we can see from the huge difference between the 3rd quartile (75%) and the maximum of each of the data samples.

4 Model and Methodology

The statistical methodoloy we use in this work was introduced by Toda and Yamamoto (1995) who showed that when one of the time series is non-stationary it is possible to do a model in levels, with the degree of integration added as an extra lag. Following the theory developed by Toda and Yamamoto, we can ignore the extra lag added by doing the Wald test, where the test statistics will follow the usual aymptotic χ^2 distribution under the null hypothesis. We include this extra lag to make sure the asymptotic properties of the statistic hold. Finally, from Toda and Yamamoto (1995) we can conclude that we can make this test when the data is either cointegrated or not.

Using the Akaike Information Criterion (AIC), we determined that an order twenty four vector autoregression VAR(24) is appropriate for the BTC and the S&P500 model. Next, we used the Ljung-Box test to see if there is autocorrelation in the residuals of the fitted values. In this test, the null hypothesis is that the data are independently distributed. From this test, we conclude that we could not reject the null hypothesis. Thus we didn't add any extra lags. Additionally, we use a lag plot, plot the autocorrelation function (ACF plot) and apply the Augmented Dickey Fuller test to conclude that our time series are not stationary (considering the relationship between the lags seen in the lag plot and the slow decrease of the plot in the autocorrelation function). In Figure 5 and Figure 6 we can see the lag plot and ACF plot of the BTC time series and the S&P 500 time series (before doing first order integration).

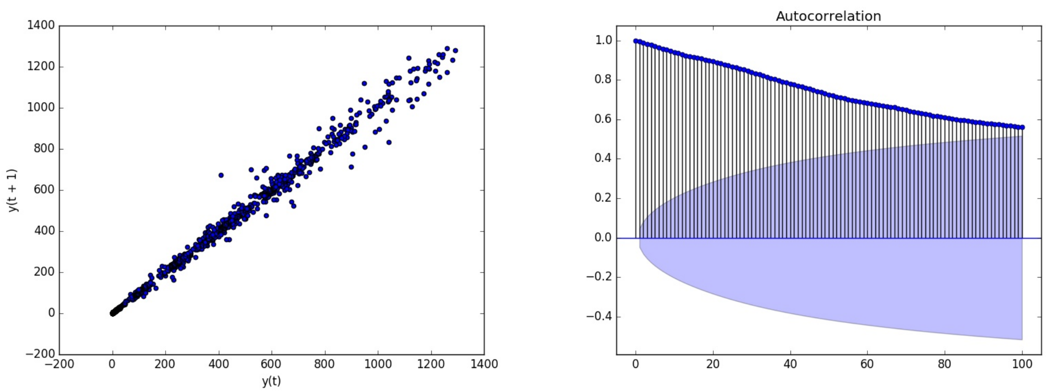

Figure 5: In these panels we do a first test to check whether the BTC is stationary. The left panel shows the lag plot of BTC which suggests non-stationarity of the series since we see clear patterns in the table. The right panel shows the ACF plot of the BTC time series which clearly suggests non-stationarity with the slow decrease of the plot.

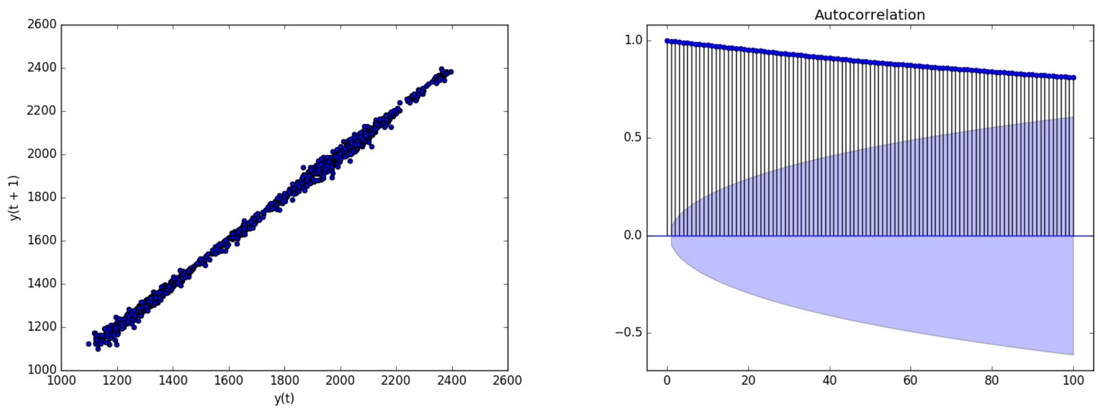

Figure 6: In these panels we do a first test to check whether the S&P 500 time series is stationary. The left panel shows the lag plot of the S&P 500 time series which suggests non-stationarity of the series since we see clear patterns in the table. The right panel shows the ACF plot of the S&P 500 time series which clearly suggests non-stationarity with the slow decrease of the plot.

We used a first-order integration (difference the time series with itself using one lag) to make our time series stationary and to prevent spurious relationships in the data. Additionally, we added an extra lag to each model to apply the theory developed by Toda and Yamamoto. After differencing, we again do the lag plot, plot the autocorrelation function, and do an Augmented Dickey Fuller Test (ADF test). We can see these plots in Figure 7 and Figure 8. This time, we can reject the ADF null hypothesis test, which tests whether the time series is not stationary. Furthermore, we observe randomness in the lag plot and an exponential decay in the autocorrelation function shown below, all of which suggests that we have stationary time series.

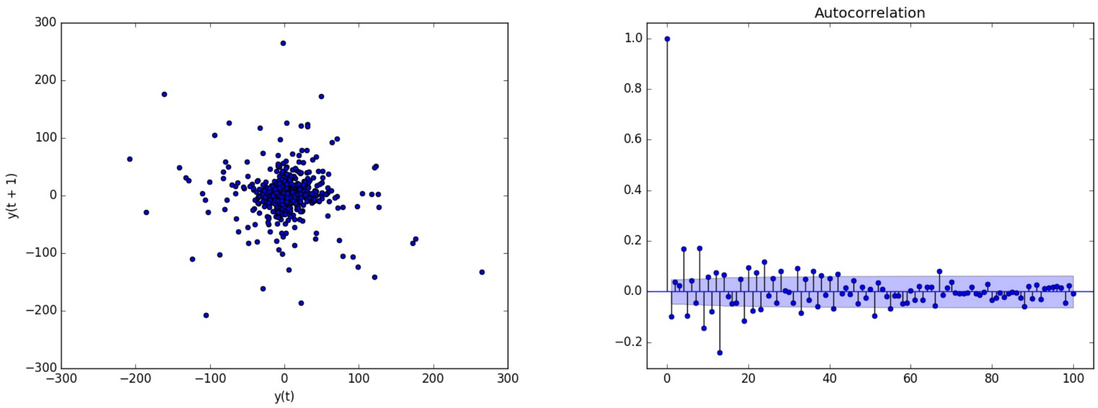

Figure 7: In these panels we do a second test to check stationarity of BTC time series after first order integration. THe left panel shows the lag plot of BTC time series which suggests stationarity of the series since we see randomness in the distribution of the points. The right panel shows the ACF plot of the BTC time series which clearly suggests stationarity of the series throught the exponential decrease of the plot.

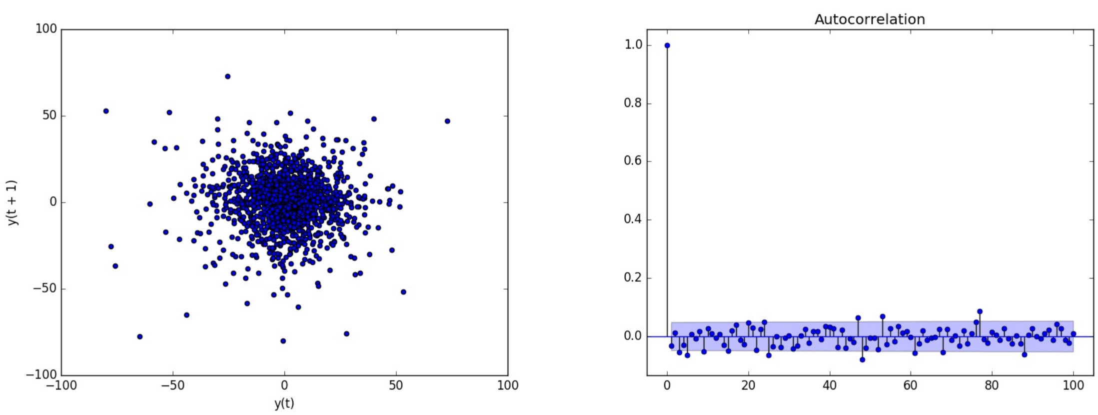

Figure 8: In these panels we do a second test to check stationarity of the S&P 500 time series after first order integration. THe left panel shows the lag plot of the S&P 500 time series which suggests stationarity of the series since we see randomness in the distribution of the points. The right panel shows the ACF plot of the S&P 500 time series which clearly suggests stationarity of the series throught the exponential decrease of the plot.

We do a similar analysis in the time series of weekly Bitcoin price, VIX and Blockchain Google Trends (BGT). We apply a first order of integration to these time series. At this point, the lag plot, the autocorrelation function, and the ADF test suggest that our time series are stationary. The interested reader can look at the lag plots and ACF plots of these time series in Appendix B. Now, for the BTC and VIX model, we conclude, with the AIC, that an order twenty four vector autoregression model VAR(24) is appropriate (but we still add the extra lag for the Toda and Yamamoto model). For the BTC_Vol and SP500 model and the BTC_Vol and VIX model we conclude, with the AIC, that an order 20 vector autoregression model VAR(20) is appropriate (and we still add the extra lag for the Toda and Yamamoto model). Finally, for the Bitcoin weekly price and BGT model we conclude, using the AIC, that an order 12 vector autoregression model VAR(12) is appropriate (again we still add the extra lag for the Toda and Yamamoto model). The particular models are:

$$BP_t = \alpha_1 + \sum_{j=1}^{25} \gamma_{1,j} BP_{t-j} + \sum_{j=1}^{25} \beta_{1,j} SP_{t-j} + \epsilon_{1,t}$$

$$SP_t = \alpha_2 + \sum_{j=1}^{25} \delta_{1,j} BP_{t-j} + \sum_{j=1}^{25} \phi_{1,j} SP_{t-j} + \epsilon_{2,t}$$

$$BP_t = \mu_1 + \sum_{j=1}^{25} \psi_{1,j} BP_{t-j} + \sum_{j=1}^{25} \omega_{1,j} SPVIX_{t-j} + \nu_{1,t}$$

$$SPVIX_t = \mu_2 + \sum_{j=1}^{25} \theta_{1,j} BP_{t-j} + \sum_{j=1}^{25} \eta_{1,j} SPVix_{t-j} + \nu_{2,t}$$

$$BPVol_t = \alpha_1^{'} + \sum_{j=1}^{21} \gamma_{1,j}^{'} BPVol_{t-j} + \sum_{j=1}^{21} \beta_{1,j}^{'} SP_{t-j} + \epsilon_{1,t}^{'}$$

$$SP_t = \alpha_2^{'} + \sum_{j=1}^{21} \delta_{1,j}^{'} BPVol_{t-j} + \sum_{j=1}^{21} \phi_{1,j}^{'} SP_{t-j} + \epsilon_{2,t}^{'}$$

$$BPVol_t = \mu_1^{'} + \sum_{j=1}^{21} \psi_{1,j}^{'} BPVol_{t-j} + \sum_{j=1}^{21} \omega_{1,j}^{'} SPVIX_{t-j} + \nu_{1,t}^{'}$$

$$SPVIX_t = \mu_2^{'} + \sum_{j=1}^{21} \theta_{1,j}^{'} BPVol_{t-j} + \sum_{j=1}^{21} \eta_{1,j}^{'} SPVix_{t-j} + \nu_{2,t}^{'}$$

$$BPWeek_t = \alpha_1^{''} + \sum_{j=1}^{13} \gamma_{1,j}^{''} BPWeek_{t-j} + \sum_{j=1}^{13} \beta_{1,j}^{''} BKCH_{t-j} + \epsilon_{1,t}^{''}$$

$$BKCH_t = \alpha_2^{''} + \sum_{j=1}^{13} \delta_{1,j}^{''} BPWeek_{t-j} + \sum_{j=1}^{13} \phi_{1,j}^{''} BKCH_{t-j} + \epsilon_{1,t}^{''}$$

where BP_t represents Bitcoin price at time t, SP_t is the value of the S&P500 at time, $BPVol_t$ is the realized volatility of Bitcoin price, $SPVIX_t$ is the implied volatility at time t, $BKCH_t$ is Google Trends at time t and $BPWeek_t$ is the weekly price of bitcoin at time t. We finished the analysis using Granger Causality test to see which variable in each model has a causation relation with the other, if any. We present the results of the analysis in the next section.

5 Results

In Appendix A we present the tables showing the results from running the VAR models specified above. In the following subsections, we present the results for the Granger-causality tests for each of the pairs of time series of interes: Bitcoin price and S&P500, Bitcoin price and S&P 500 VIX, Bitcoin price realized volatility and S&P 500, Bitcoin price realized volatility and S&P 500 VIX and Bitcoin price and Blockchain Google Trends.

5.1 Bitcoin price and S&P 500

From Appendix A, we can see from Table A1 the VAR coefficient estimates of the effect of S&P 500 on BTC and from Table A2 the VAR coefficient estimates of the effect of BTC on S&P500. We interpret the coefficients in the table as follows: a 1% increase in Bitcoin Price at $t-1$ there is a decrease of 0.0355% in Bitcoin price at time t, following the results shown in table A1. We can observe that we do not have many significant coefficients, but for this work we are actually interested in the usefulness of one time series for forecasting the other one, i.e. Granger causality. With the Granger causality test we are testing whether knowing past values of time series X together with past values of time series Y can be used together to make better predictions of time series Y as opposed to only using past values of time series Y.

The result of the Granger causality test is shown in Table 3 and Table 4. We show the results when testing whether BTC price Granger-causes S&P 500 or S&P 500 Granger causes BTC.

Table 3: Granger causality from S&P500 to Bitcoin price

H_0: 'BitCoin Price' do not Granger-cause S&P500.

Test statistic	Critical Value	p-value	df
23.465636	37.652484	0.550	25

Conclusion: fail to reject H_0 at 5% significance leve.

Table 4: Granger causality from Bitcoin price on S&P500

H_0: 'Close S&P500' do not Granger-cause BitCoin Price.

Test statistic	Critical value	p-value	df
28.421991	37.652484	0.289	25

Conclusion: fail to reject H_0 at 5% significance level.

From the results of the Granger causality test, we can see that neither BTC Granger causes S&P500 nor S&P500 Granger causes BTC. Notice we reject the null hypothesis of Granger causality both at the 5% and 10% significance level. This result agrees with the results published by Ciaian et al. (2014) who, following a similar econometric approach as we do, don't find evidence that financial variables like Dow Jones index have some impact on Bitcoin price. In a different study, van Wijk (2013) does find a somewhat contradictory result with ours since they find that Dow Jones does have some effect on Bitcoin price. However, van Wijk uses a different econometric approach, simple OLS regression, and so the source of discrepancy might come from this different approaches.

5.2 Bitcoin price and VIX

In tables A3 and A4 we see the VAR coefficient estimates of the effect of S&P500 VIX on Bitcoin price and the VAR coefficient estimates of the effect of Bitcoin price on S&P500 VIX respectively. In this case, we interpret the coefficients in the same way as we did in tables A1 and A2. Furthermore, in Table 5 and Table 6 shown below, we see the results of the Granger causality test. Particularly, we are testing whether Bitcoin price Granger-causes the VIX.

Table 5: Granger causality test from Bitcoin price to VIX

H_0: 'BitCoin Price' do not Granger-cause VIX.

Test statistic	Critical value	p-value	df
13.086809	37.652484	0.975	25

Conclusion: fail to reject H_0 at 5.00% significance level

Table 6: Granger causality test from VIX to BTC

H_0: 'VIX ' do not Granger-cause BitCoin Price.

Test statistic	Critical value	p-value	df
15.565252	37.652484	0.927	25

Conclusion: fail to reject H_0 at 5% significance level

From these results, we can see that predictions of BTC using VIX past data together with past BTC data are not better than just using BTC data. Similarly, we can see that predictions of VIX using VIX past data together with past BTC data are not better than just using VIX data. These results, together with Ciaian et al. (2014) suggest that to predict Bitcoin price or find causal relations between Bitcoin price and financial variables we should look at other financial instruments besides Dow Jones or S&P 500. Since Bitcoin mining is mainly done by Chinese companies, perhaps one suggestion for further research would be to do similar analysis but with indexes formed by Chinese companies or companies that operate or accept payments with Bitcoin.

5.3 Bitcoin price realized volatility and S&P 500

In Table A5 and Table A6 we can see the VAR coefficient estimates of the effect of Bitcoin price realized volatility on S&P 500 and the VAR coefficient estimates of the effect of Bitcoin price realized volatility on S&P 500 respectively. In Table 7 and Table 8 below we present the results from the Granger-causality test ran on the time series Bitcoin price realized volatility and S&P 500. Particularly, we are interested in seeing whether one of these time series Granger-causes the other.

Table 7: Granger causality test from S&P500 on BTC_Vol.

H_0: 'S&P500' do not Granger-cause BTC_Vol

Test statistic	Critical value	p-value	df
17.740966	32.670573	0.665	21

Conclusion: fail to reject H_0 at 5% significance level.

Table 8: Granger causality test from Bitcoin price realized volatility on S&P500

H_0: 'Bitcoin price realized volatility' do not Granger-cause S&P500

Test statistic	Critical value	p-value	df
47.014349	32.670573	0.001	21

Conclusion: reject H_0 at 5% significance level.

From these tables, we can see that Bitcoin price realized volatility Granger-causes S&P500 but S&P500 does not Granger-cause Bitcoin price realized volatility. This results are consistent with the results found by Bourie et al. (2016) which show that Bitcoin price realized volatility have a negative relation with S&P 500 implied volatility (VIX). Since the Granger-causality test show us a Granger-causation from Bitcoin price realized volatility to S&P 500, and considering the results from Bourie et al. (2016) regarding Bitcoin realized volatility and VIX, we can expect a significant causation between VIX and Bitcoin price volatility.

5.4 Bitcoin price realized volatility and S&P 500 VIX

In Table A7 and Table A8 we see the VAR coefficient estimates of the effect of S&P 500 VIX on Bitcoin price realized volatility and the VAR coefficient estimates of the effect of Bitcion price realized volatlity on S&P 500 VIX respectively. Furthermore, in Table 9 and Table 10 below we show the results of running Granger-causality tests on the corresponding time series.

Table 9: Granger causality from Bitcoin realized volatility on VIX

H_0: 'Bitcoin price realized volatility' do not Granger-cause VIX

Test statistic	Critical value	p-value	df
53.221793	32.670573	0.000	21

Conclusion: reject H_0 at 5% significance level.

Table 10: Granger causality from VIX on Bitcoin realized volatility

H_0: 'S&P 500 VIX' do not Granger-cause Bitcoin price realized volatility

Test statistic	Critical value	p-value	df
33.284287	32.670573	0.043	21

Conclusion: reject H_0 at 5% significance level.

In both of these Granger-causality tests we reject the null hypothesis and thus we can conclude that Bitcoin price realized volatility Granger-causes the VIX and the VIX Granger-causes Bitcoin price realized volatility. The negative relation between Bitcoin price realized volatility and S&P500 found by Bourie et al. (2016) coincides with the Granger-causality found between these time series in this work. Notice that the Bitcoin price realized volatility Granger-causes S&P 500 VIX with a stronger relationship than S&P 500 VIX Grange-causes

Bitcoin price realized volatility. On the one hand, this causality relationship could suggest that negative movements in the financial markets make investors turn to new assets, one of which would be Bitcoin, thus affecting Bitcoin price realized volatility. On the other hand, these results also suggest that brusque movements in Bitcoin price (such as Mt. Gox meltdown) could scare investors and make them go to better studied financial assets. Furthermore, this implies that S&P 500 VIX could be a useful tool for forecasting periods of Bitcoin price volatility and similarly Bitcoin price volatility could be a usefull tool for forecasting periods of volatility in S&P 500 VIX.

5.5 Bitcoin price and Blockchain Google Trends

In this section, we see focus on the relationship between Bitcoin price and Blockchain Google Trends. In the tables appendix we see in Table A9 and Table A10 the VAR coefficient estimates of the effect of Blockchain Google trends on Bitcoin price and the VAR coefficient estimates of the effect of Bitcoin price on Blockchain Google Trends. As in the cases above, we do not focus on the statistical significance of the coefficient estimates, but rather on the results of the Granger-causality test shown below in Table 11 and Table 12.

Table 11: Granger causality from BGT to Bitcoin weekly price

H_0: 'Blockchain' does not Granger-cause Bitcoin weekly price.

Test statistic	Critical value	p-value	df
13.86	22.36	0.384	13

Conclusion: Fail to reject H_0 at 5% significance level.

Table 12: Granger causality test from Bitcoin weekly price on BGT

H_0: 'Close Bitcoin Price weekly' do not Granger-cause Blockchain trends

Test statistic	Critical value	p-value	df
21.636137	22.362032	0.061	13

Conclusion: fail to reject H_0 at 5% significance level, but reject H_0 at 10% significance level

From these results, we conclude that the use of past Bitcoin weekly (BTCweek) prices together with BGT data does not provide better predictions of BTCweek prices than just using past BTCweek prices. On the other hand, we can conclude that using past BGT data together with past BTCweek prices provide better predictions of BGT data than just using past BGT data, at least at the 10% significant level. On the one hand, we see a Granger-causation relationship going from Bitcoin price to Blockchain trends since Bitcoin is one of the most famous applications of the Blockchain technology and so it could be one of the main determinants of Google searches regarding Blockchain. Continuing with this idea, variations in Bitcoin price could trigger the curiosity of investors and companies about Bitcoin in general and hence the Blockchain technology. On the other hand, we do not see a Granger-causality relationship going from Blockchain Google Trends to Bitcoin's price because there are probably many more determinants of Bitcoin's price than just searches about Blockchain on Google.

6 Conclusion

In this paper we showed relationships between Bitcoin price realized volatility and the S&P 500, between Bitcoin price realized volatility and the VIX and between Bitcoin price and Blockchain Google Trends. In our analysis we found no statistically significant Granger-causality when analyzing the time series of BTC and the S&P 500 and BTC and the VIX. These results suggest Bitcoin price has no causal relationships to financial instruments such as S&P 500 and they are consistent with the findings of Ciaian et al. (2014).

The Granger causality test applied on the BTC_Vol and S&P 500 time series show that BTC_Vol Granger-causes S&P 500 at the 5% significant level. This result suggests that studying BTC_Vol provides insight into understanding better the behavior of the S&P 500. This Granger-causality follows the results previously found by Bourie et al. (2016) and contributes to their results that there exist a negative relationship between BTC_Vol and the VIX.

The causality analysis done with the BTC_Vol and the VIX time series show there exist Granger-causality in both directions between these two series, with the Granger-causality of BTC_Vol on the VIX being the strongest one in terms of significance level. These results support the results showing negative relations between BTC_Vol and the VIX. Furthermore, the results show that in order to understand the volatility of either of this topics we can try to understand the other one and gain information about both.

The Granger-causality test we ran on the Bitcoin weekly price and BGT time series show that Bitcoin price Granger-causes BGT at the 10% significant level. However, we do not find a Granger-causal relationship in the other direction. This result suggests that changes in Bitcoin price could trigger the curiosity of investors and companies on the cryptocurrency and eventually in the Blockchain technology, thus affecting the number of searches containing Blockchain. This supposition seems reasonable since Bitcoin is one of the most popular applications of Blockchain whereas Blockchain queries might not be very related to Bitcoin price.

The information presented in this work could be useful primarily for investors, regulators and governments that are interested in the Bitcoin market and how it could affect the financial markets in the future. We provide results that link Bitcoin price volatility with volatility of financial indexes, like the S&P 500 that could eventually provide ways to understand the Bitcoin market. Regulators and governments could be interested in this information to make better regulations for Bitcoin users and companies that now accept this type of cryptocurrency. Furthermore, investors could be interested in these results in order to use Bitcoin price as a proxy of the volatility of the market and guide their future investments according to this information.

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Appendix A Regression tables

Table A1: VAR estimates of effect of S&P500 on Bitcoin price

Explanatory Variable	**Dependent Variable**	**p-value**
const	0.346909	0.530
L1 BitCoin Price	-0.035539	0.158
L1 Close S&P500	0.050259	0.161
L2 BitCoin Price	-0.009357	0.709
L2 Close S&P500	0.017347	0.628
L3 BitCoin Price	0.059607	0.018
L3 Close S&P500	0.044598	0.213
L4 BitCoin Price	0.122123	0.000***
L4 Close S&P500	-0.030484	0.395
L5 BitCoin Price	-0.040345	0.111
L5 Close S&P500	0.071953	0.045**
L6 BitCoin Price	0.004890	0.847
L6 Close S&P500	0.019931	0.579
L7 BitCoin Price	-0.030306	0.230
L7 Close S&P500	0.008221	0.819
L8 BitCoin Price	0.149557	0.000***
L8 Close S&P500	0.104648	0.004***
L9 BitCoin Price	-0.076022	0.003***
L9 Close S&P500	0.012707	0.723

Table A1: VAR estimates of effect of S&P500 on Bitcoin price

Explanatory Variable	**Dependent Variable**	**p-value**
L10 BitCoin Price	0.026126	0.307
L10 Close S&P500	0.047093	0.190
L11 BitCoin Price	-0.043778	0.087*
L11 Close S&P500	0.013558	0.706
L12 BitCoin Price	0.008466	0.741
L12 Close S&P500	0.009935	0.782
L13 BitCoin Price	-0.185926	0.000***
L13 Close S&P500	0.016546	0.644
L14 BitCoin Price	0.005003	0.846
L14 Close S&P500	0.042284	0.238
L15 BitCoin Price	0.048400	0.061*
L15 Close S&P500	-0.046173	0.197
L16 BitCoin Price	-0.103178	0.000***
L16 Close S&P500	0.023925	0.505
L17 BitCoin Price	0.048423	0.063*
L17 Close S&P500	-0.006573	0.854
L18 BitCoin Price	-0.031091	0.228
L18 Close S&P500	0.048761	0.174
L19 BitCoin Price	-0.059717	0.021**
L19 Close S&P500	0.008363	0.816

Table A1: VAR estimates of effect of S&P500 on Bitcoin price

Explanatory Variable	**Dependent Variable**	**p-value**
L20 BitCoin Price	0.063489	0.015**
L20 Close S&P500	-0.013975	0.697
L21 BitCoin Price	-0.012589	0.632
L21 Close S&P500	0.009892	0.783
L22 BitCoin Price	0.022088	0.398
L22 Close S&P500	-0.047212	0.188
L23 BitCoin Price	-0.029690	0.255
L23 Close S&P500	0.038348	0.284
L24 BitCoin Price	0.102110	0.000***
L24 Close S&P500	-0.021875	0.541
L25 BitCoin Price	0.022431	0.399
L25 Close S&P500	0.032929	0.358

$^{*}p < 0.1;^{**}p < 0.05;^{***}p < 0.01$

Table A2: VAR estimates of effect of Bitcoin price on S&P500

Explanatory Variable	**Dependent Variable**	**p-value**
const	0.882354	0.023**
L1BitCoin Price	0.016775	0.342
L1 Close S&P500	-0.025446	0.311
L2 BitCoin Price	0.004525	0.797
L2 Close S&P500	0.017987	0.474

Table A2: VAR estimates of effect of Bitcoin price on S&P500

Explanatory Variable	**Dependent Variable**	**p-value**
L3 BitCoin Price	0.002636	0.881
L3 Close S&P500	-0.063290	0.012**
L4 BitCoin Price	0.018611	0.290
L4 Close S&P500	-0.041686	0.097*
L5 BitCoin Price	0.006675	0.707
L5 Close S&P500	-0.056727	0.024**
L6 BitCoin Price	-0.009434	0.595
L6 Close S&P500	0.000008	1.000
L7 BitCoin Price	-0.012582	0.477
L7 Close S&P500	-0.021450	0.393
L8 BitCoin Price	-0.011006	0.534
L8 Close S&P500	0.011704	0.641
L9 BitCoin Price	-0.026228	0.144
L9 Close S&P500	-0.052878	0.036**
L10 BitCoin Price	-0.005497	0.759
L10 Close S&P500	0.008765	0.728
L11 BitCoin Price	0.041793	0.020**
L11 Close S&P500	0.010877	0.666
L12 BitCoin Price	-0.023685	0.187
L12 Close S&P500	-0.009004	0.720
L13 BitCoin Price	0.008585	0.627
L13 Close S&P500	0.002879	0.909
L14 BitCoin Price	-0.008025	0.656
L14 Close S&P500	-0.041186	0.101
L15 BitCoin Price	0.007584	0.676
L15 Close S&P500	-0.042918	0.088*

Table A2: VAR estimates of effect of Bitcoin price on S&P500

Explanatory Variable	**Dependent Variable**	**p-value**
L16 BitCoin Price	-0.000676	0.970
L16 Close S&P500	0.015587	0.535
L17 BitCoin Price	0.009713	0.595
L17 Close S&P500	0.044317	0.077*
L18 BitCoin Price	0.041371	0.022**
L18 Close S&P500	-0.021763	0.386
L19 BitCoin Price	-0.017836	0.325
L19 Close S&P500	-0.034067	0.175
L20 BitCoin Price	0.003063	0.868
L20 Close S&P500	0.049380	0.050**
L21 BitCoin Price	-0.011427	0.536
L21 Close S&P500	0.032114	0.201
L22 BitCoin Price	-0.017627	0.336
L22 Close S&P500	-0.048559	0.053*
L23 BitCoin Price	-0.024190	0.186
L23 Close S&P500	0.019571	0.436
L24 BitCoin Price	0.011194	0.546
L24 Close S&P500	0.050528	0.044**
L25 BitCoin Price	0.010998	0.555
L25 Close S&P500	-0.058741	0.020**

$^{*}p < 0.1;^{**}p < 0.05;^{***}p < 0.01$

Table A3: VAR estimates of effect of S&P500VIX on Bitcoin price

Explanatory Variable	**Dependent Variable**	**p-value**
const	0.638556	0.233
L1 BitCoin Price	-0.037283	0.139
L1 S&P 500 VIX Close	-0.343880	0.333
L2 BitCoin Price	-0.005318	0.832
L2 S&P 500 VIX Close	-0.037736	0.916
L3 BitCoin Price	0.060535	0.016**
L3 S&P 500 VIX Close	0.109589	0.758
L4 BitCoin Price	0.122936	0.000***
L4 S&P 500 VIX Close	0.167968	0.640
L5 BitCoin Price	-0.035997	0.155
L5 S&P 500 VIX Close	-0.646193	0.073*
L6 BitCoin Price	0.007310	0.773
L6 S&P 500 VIX Close	-0.304426	0.401
L7 BitCoin Price	-0.027768	0.271
L7 S&P 500 VIX Close	-0.235867	0.514
L8 BitCoin Price	0.148364	0.000***
L8 S&P 500 VIX Close	-0.558140	0.124
L9 BitCoin Price	-0.073612	0.004***
L9 S&P 500 VIX Close	-0.061091	0.866
L10 BitCoin Price	0.023469	0.359
L10 S&P 500 VIX Close	-0.271771	0.455
L11 BitCoin Price	-0.042272	0.098*
L11 S&P 500 VIX Close	-0.251775	0.489
L12 BitCoin Price	0.010246	0.689
L12 S&P 500 VIX Close	-0.326034	0.369
L13 BitCoin Price	-0.184771	0.000***

Table A3: VAR estimates of effect of S&P500VIX on Bitcoin price

Explanatory Variable	**Dependent Variable**	**p-value**
L13 S&P 500 VIX Close	-0.184781	0.612
L14 BitCoin Price	0.004682	0.855
L14 S&P 500 VIX Close	-0.247865	0.495
L15 BitCoin Price	0.048425	0.061*
L15 S&P 500 VIX Close	0.049807	0.891
L16 BitCoin Price	-0.100744	0.000***
L16 S&P 500 VIX Close	-0.510903	0.160
L17 BitCoin Price	0.046112	0.077*
L17 S&P 500 VIX Close	0.033040	0.927
L18 BitCoin Price	-0.027947	0.279
L18 S&P 500 VIX Close	-0.394054	0.277
L19 BitCoin Price	-0.057168	0.027**
L19 S&P 500 VIX Close	-0.263561	0.466
L20 BitCoin Price	0.065249	0.013**
L20 S&P 500 VIX Close	-0.099716	0.783
L21 BitCoin Price	-0.010648	0.686
L21 S&P 500 VIX Close	-0.233444	0.517
L22 BitCoin Price	0.021246	0.417
L22 S&P 500 VIX Close	0.361729	0.314
L23 BitCoin Price	-0.030241	0.247
L23 S&P 500 VIX Close	-0.359835	0.312
L24 BitCoin Price	0.102687	0.000***
L24 S&P 500 VIX Close	0.375909	0.292
L25 BitCoin Price	0.023329	0.380
L25 S&P 500 VIX Close	-0.125211	0.724

$^{*}p < 0.1;^{**}p < 0.05;^{***}p < 0.01$

Table A4: VAR estimates of effect of S&P500VIX on Bitcoin price

Explanatory Variable	**Dependent Variable**	**p-value**
const	-0.008164	0.830
L1 BitCoin Price	-0.000105	0.953
L1 S&P 500 VIX Close	-0.102378	0.000***
L2 BitCoin Price	-0.000325	0.855
L2 S&P 500 VIX Close	-0.030952	0.221
L3 BitCoin Price	-0.001141	0.521
L3 S&P 500 VIX Close	-0.144582	0.000***
L4 BitCoin Price	0.000722	0.685
L4 S&P 500 VIX Close	-0.069673	0.006***
L5 BitCoin Price	-0.000365	0.839
L5 S&P 500 VIX Close	-0.109939	0.000***
L6 BitCoin Price	0.001533	0.393
L6 S&P 500 VIX Close	-0.008977	0.727
L7 BitCoin Price	0.001499	0.402
L7 S&P 500 VIX Close	-0.090615	0.000***
L8 BitCoin Price	-0.000110	0.951
L8 S&P 500 VIX Close	-0.006341	0.805
L9 BitCoin Price	0.002548	0.160
L9 S&P 500 VIX Close	-0.063567	0.014
L10 BitCoin Price	-0.000154	0.933
L10 S&P 500 VIX Close	0.013037	0.613
L11 BitCoin Price	-0.002492	0.169
L11 S&P 500 VIX Close	0.007280	0.778
L12 BitCoin Price	0.001048	0.564
L12 S&P 500 VIX Close	-0.073999	0.004***
L13 BitCoin Price	-0.000589	0.741

Table A4: VAR estimates of effect of S&P500VIX on Bitcoin price

Explanatory Variable	**Dependent Variable**	**p-value**
L13 S&P 500 VIX Close	-0.027324	0.289
L14 BitCoin Price	0.001864	0.306
L14 S&P 500 VIX Close	-0.050374	0.050**
L15 BitCoin Price	-0.000629	0.731
L15 S&P 500 VIX Close	-0.030775	0.232
L16 BitCoin Price	-0.001310	0.475
L16 S&P 500 VIX Close	-0.009477	0.713
L17 BitCoin Price	-0.000737	0.689
L17 S&P 500 VIX Close	0.016742	0.515
L18 BitCoin Price	-0.002053	0.262
L18 S&P 500 VIX Close	-0.026783	0.298
L19 BitCoin Price	0.001855	0.311
L19 S&P 500 VIX Close	-0.047706	0.063*
L20 BitCoin Price	0.001224	0.510
L20 S&P 500 VIX Close	0.059216	0.021**
L21 BitCoin Price	0.000747	0.689
L21 S&P 500 VIX Close	-0.014279	0.576
L22 BitCoin Price	0.000653	0.725
L22 S&P 500 VIX Close	-0.041979	0.099*
L23 BitCoin Price	0.001920	0.299
L23 S&P 500 VIX Close	0.057288	0.023**
L24 BitCoin Price	-0.002328	0.214
L24 S&P 500 VIX Close	0.023085	0.361
L25 BitCoin Price	-0.000200	0.916
L25 S&P 500 VIX Close	-0.011527	0.647

$^{*}p < 0.1;^{**}p < 0.05;^{***}p < 0.01$

Table A5: VAR estimates of effect of Bitcoin price realized volatility on S&P 500

Explanatory Variable	**Dependent Variable**	**p-value**
const	-0.000014	0.909
L1 Bitcoin/USD historical volatility	0.154672	0.000***
L1 Close S&P500	0.000002	0.828
L2 Bitcoin/USD historical volatility	0.044661	0.069*
L2 Close S&P500	0.000007	0.367
L3 Bitcoin/USD historical volatility	0.047873	0.051*
L3 Close S&P500	-0.000007	0.392
L4 Bitcoin/USD historical volatility	0.020243	0.404
L4 Close S&P500	-0.000001	0.913
L5 Bitcoin/USD historical volatility	0.033410	0.169
L5 Close S&P500	-0.000003	0.699
L6 Bitcoin/USD historical volatility	0.004568	0.851
L6 Close S&P500	-0.000000	0.953
L7 Bitcoin/USD historical volatility	0.028762	0.237
L7 Close S&P500	-0.000001	0.923
L8 Bitcoin/USD historical volatility	0.025020	0.304
L8 Close S&P500	-0.000013	0.107
L9 Bitcoin/USD historical volatility	0.007582	0.756
L9 Close S&P500	-0.000001	0.941
L10 Bitcoin/USD historical volatility	0.016507	0.498
L10 Close S&P500	-0.000002	0.796
L11 Bitcoin/USD historical volatility	0.027305	0.262
L11 Close S&P500	0.000003	0.657
L12 Bitcoin/USD historical volatility	0.007736	0.751
L12 Close S&P500	0.000006	0.450
L13 Bitcoin/USD historical volatility	0.004096	0.867

Table A5: VAR estimates of effect of Bitcoin price realized volatility on S&P 500

Explanatory Variable	Dependent Variable	p-value
L13 Close S&P500	0.000010	0.200
L14 Bitcoin/USD historical volatility	0.030434	0.211
L14 Close S&P500	-0.000001	0.903
L15 Bitcoin/USD historical volatility	-0.011054	0.650
L15 Close S&P500	-0.000006	0.416
L16 Bitcoin/USD historical volatility	0.014794	0.544
L16 Close S&P500	0.000005	0.565
L17 Bitcoin/USD historical volatility	0.016738	0.492
L17 Close S&P500	0.000011	0.176
L18 Bitcoin/USD historical volatility	-0.037966	0.119
L18 Close S&P500	0.000008	0.296
L19 Bitcoin/USD historical volatility	-0.065538	0.007***
L19 Close S&P500	-0.000012	0.140
L20 Bitcoin/USD historical volatility	-0.247726	0.000***
L20 Close S&P500	0.000013	0.101
L21 Bitcoin/USD historical volatility	-0.004784	0.848
L21 Close S&P500	-0.000009	0.253

$^{*}p < 0.1;^{**} p < 0.05;^{***} p < 0.01$

Table A6: VAR estimates of effect of S&P 500 on Bitcoin price realized volatility

Explanatory Variable	Dependent Variable	p-value
const	0.856812	0.024
L1 Bitcoin/USD historical volatility	-5.768691	0.942
L1 Close S&P500	-0.033298	0.184

Table A6: VAR estimates of effect of S&P 500 on Bitcoin price realized volatility

Explanatory Variable	**Dependent Variable**	**p-value**
L2 Bitcoin/USD historical volatility	-168.844724	0.030**
L2 Close S&P500	0.000343	0.989
L3 Bitcoin/USD historical volatility	227.285605	0.004***
L3 Close S&P500	-0.043181	0.085*
L4 Bitcoin/USD historical volatility	-149.619658	0.052*
L4 Close S&P500	-0.046927	0.061*
L5 Bitcoin/USD historical volatility	152.372861	0.048*
L5 Close S&P500	-0.066340	0.008***
L6 Bitcoin/USD historical volatility	-73.932318	0.338
L6 Close S&P500	-0.007298	0.771
L7 Bitcoin/USD historical volatility	35.484590	0.645
L7 Close S&P500	-0.014074	0.574
L8 Bitcoin/USD historical volatility	-206.075455	0.008***
L8 Close S&P500	0.006993	0.780
L9 Bitcoin/USD historical volatility	-22.941605	0.767
L9 Close S&P500	-0.058429	0.020**
L10 Bitcoin/USD historical volatility	-27.530695	0.722
L10 Close S&P500	0.012837	0.608
L11 Bitcoin/USD historical volatility	162.326105	0.036**
L11 Close S&P500	0.015192	0.543
L12 Bitcoin/USD historical volatility	138.807669	0.073*
L12 Close S&P500	-0.009030	0.718
L13 Bitcoin/USD historical volatility	49.501420	0.522
L13 Close S&P500	0.004480	0.858
L14 Bitcoin/USD historical volatility	-104.587563	0.176
L14 Close S&P500	-0.036651	0.142

Table A6: VAR estimates of effect of S&P 500 on Bitcoin price realized volatility

Explanatory Variable	**Dependent Variable**	**p-value**
L15 Bitcoin/USD historical volatility	29.473153	0.703
L15 Close S&P500	-0.048375	0.053*
L16 Bitcoin/USD historical volatility	112.789268	0.145
L16 Close S&P500	0.020476	0.412
L17 Bitcoin/USD historical volatility	87.863116	0.256
L17 Close S&P500	0.039140	0.116
L18 Bitcoin/USD historical volatility	96.437147	0.212
L18 Close S&P500	-0.014086	0.572
L19 Bitcoin/USD historical volatility	55.200271	0.475
L19 Close S&P500	-0.028964	0.243
L20 Bitcoin/USD historical volatility	73.741978	0.341
L20 Close S&P500	0.058503	0.019**
L21 Bitcoin/USD historical volatility	-106.246749	0.178
L21 Close S&P500	0.036844	0.139

$^{*}p < 0.1;^{**}p < 0.05;^{***}p < 0.01$

Table A7: VAR estimates of effect of S&P 500 VIX on Bitcoin price realized volatility

Explanatory Variable	**Dependent Variable**	**p-value**
const	-0.000008	0.944
L1 Bitcoin/USD historical volatility	0.156292	0.000***
L1 S&P 500 VIX Close	-0.000014	0.853
L2 Bitcoin/USD historical volatility	0.047511	0.054*
L2 S&P 500 VIX Close	-0.000017	0.824
L3 Bitcoin/USD historical volatility	0.048506	0.049**

Table A7: VAR estimates of effect of S&P 500 VIX on Bitcoin price realized volatility

Explanatory Variable	Dependent Variable	p-value
L3 S&P 500 VIX Close	0.000043	0.585
L4 Bitcoin/USD historical volatility	0.019147	0.431
L4 S&P 500 VIX Close	0.000062	0.434
L5 Bitcoin/USD historical volatility	0.037683	0.121
L5 S&P 500 VIX Close	-0.000042	0.594
L6 Bitcoin/USD historical volatility	-0.001103	0.964
L6 S&P 500 VIX Close	-0.000002	0.977
L7 Bitcoin/USD historical volatility	0.033170	0.172
L7 S&P 500 VIX Close	0.000001	0.988
L8 Bitcoin/USD historical volatility	0.018931	0.435
L8 S&P 500 VIX Close	0.000055	0.489
L9 Bitcoin/USD historical volatility	0.013139	0.589
L9 S&P 500 VIX Close	-0.000024	0.763
L10 Bitcoin/USD historical volatility	0.013374	0.582
L10 S&P 500 VIX Close	0.000030	0.703
L11 Bitcoin/USD historical volatility	0.027710	0.253
L11 S&P 500 VIX Close	0.000007	0.926
L12 Bitcoin/USD historical volatility	0.007493	0.758
L12 S&P 500 VIX Close	-0.000136	0.086
L13 Bitcoin/USD historical volatility	0.005974	0.806
L13 S&P 500 VIX Close	-0.000172	0.031
L14 Bitcoin/USD historical volatility	0.034182	0.159
L14 S&P 500 VIX Close	-0.000054	0.496
L15 Bitcoin/USD historical volatility	-0.014261	0.557
L15 S&P 500 VIX Close	0.000147	0.065*
L16 Bitcoin/USD historical volatility	0.016283	0.503

Table A7: VAR estimates of effect of S&P 500 VIX on Bitcoin price realized volatility

Explanatory Variable	**Dependent Variable**	**p-value**
L16 S&P 500 VIX Close	0.000067	0.397
L17 Bitcoin/USD historical volatility	0.014535	0.549
L17 S&P 500 VIX Close	-0.000166	0.036**
L18 Bitcoin/USD historical volatility	-0.039822	0.101
L18 S&P 500 VIX Close	-0.000060	0.447
L19 Bitcoin/USD historical volatility	-0.065602	0.007***
L19 S&P 500 VIX Close	0.000141	0.071*
L20 Bitcoin/USD historical volatility	-0.244464	0.000***
L20 S&P 500 VIX Close	-0.000174	0.026**
L21 Bitcoin/USD historical volatility	-0.007615	0.759
L21 S&P 500 VIX Close	0.000113	0.145

$^{*}p < 0.1;^{**}p < 0.05;^{***}p < 0.01$

Table A8: VAR estimates of effect of Bitcoin price realized volatility on S&P 500 VIX.

Explanatory Variable	**Dependent Variable**	**p-value**
const	-0.006033	0.870
L1 Bitcoin/USD historical volatility	-7.368185	0.362
L1 S&P 500 VIX Close	-0.103939	0.000***
L2 Bitcoin/USD historical volatility	29.111088	0.000***
L2 S&P 500 VIX Close	-0.051783	0.040**
L3 Bitcoin/USD historical volatility	-16.744122	0.034**
L3 S&P 500 VIX Close	-0.129832	0.000***
L4 Bitcoin/USD historical volatility	6.018425	0.441
L4 S&P 500 VIX Close	-0.072601	0.004***

Table A8: VAR estimates of effect of Bitcoin price realized volatility on S&P 500 VIX.

Explanatory Variable	**Dependent Variable**	**p-value**
L5 Bitcoin/USD historical volatility	-9.793394	0.210
L5 S&P 500 VIX Close	-0.112837	0.000***
L6 Bitcoin/USD historical volatility	4.216946	0.589
L6 S&P 500 VIX Close	-0.020900	0.413
L7 Bitcoin/USD historical volatility	-5.139365	0.510
L7 S&P 500 VIX Close	-0.092689	0.000***
L8 Bitcoin/USD historical volatility	23.560062	0.003***
L8 S&P 500 VIX Close	-0.014031	0.584
L9 Bitcoin/USD historical volatility	-1.494622	0.848
L9 S&P 500 VIX Close	-0.066879	0.009***
L10 Bitcoin/USD historical volatility	3.235346	0.678
L10 S&P 500 VIX Close	0.015795	0.537
L11 Bitcoin/USD historical volatility	-15.477236	0.047**
L11 S&P 500 VIX Close	0.004407	0.863
L12 Bitcoin/USD historical volatility	-7.377266	0.345
L12 S&P 500 VIX Close	-0.076691	0.003***
L13 Bitcoin/USD historical volatility	-1.832637	0.814
L13 S&P 500 VIX Close	-0.027650	0.279
L14 Bitcoin/USD historical volatility	7.374350	0.345
L14 S&P 500 VIX Close	-0.051459	0.044**
L15 Bitcoin/USD historical volatility	1.482747	0.849
L15 S&P 500 VIX Close	-0.028941	0.256
L16 Bitcoin/USD historical volatility	-6.458997	0.408
L16 S&P 500 VIX Close	-0.009462	0.711
L17 Bitcoin/USD historical volatility	-10.701446	0.170
L17 S&P 500 VIX Close	0.013906	0.583

Table A8: VAR estimates of effect of Bitcoin price realized volatility on S&P 500 VIX.

Explanatory Variable	**Dependent Variable**	**p-value**
L18 Bitcoin/USD historical volatility	-15.791180	0.043**
L18 S&P 500 VIX Close	-0.022725	0.369
L19 Bitcoin/USD historical volatility	-12.855486	0.100*
L19 S&P 500 VIX Close	-0.042682	0.088*
L20 Bitcoin/USD historical volatility	-12.148251	0.121
L20 S&P 500 VIX Close	0.066018	0.008***
L21 Bitcoin/USD historical volatility	18.132760	0.023**
L21 S&P 500 VIX Close	-0.014600	0.559

$^{*}p < 0.1;^{**} p < 0.05;^{***} p < 0.01$

Table A9: VAR estimates of effect of Blockchain Google Trends on Bitcoin weekly price

Explanatory Variable	Dependent Variable	p-value
const	2.083532	0.598
L1 Close Bitcoin Price weekly	0.064886	0.354
L1 Blockchain	1.758885	0.136
L2 Close Bitcoin Price weekly	0.007867	0.913
L2 Blockchain	0.909175	0.473
L3 Close Bitcoin Price weekly	-0.100002	0.166
L3 Blockchain	2.125959	0.092*
L4 Close Bitcoin Price weekly	-0.173118	0.017**
L4 Blockchain	1.014777	0.424
L5 Close Bitcoin Price weekly	0.209037	0.004***
L5 Blockchain	0.825161	0.514
L6 Close Bitcoin Price weekly	0.037948	0.609
L6 Blockchain	2.075206	0.099*
L7 Close Bitcoin Price weekly	0.046921	0.526
L7 Blockchain	1.945779	0.125
L8 Close Bitcoin Price weekly	-0.075838	0.306
L8 Blockchain	-0.551732	0.669
L9 Close Bitcoin Price weekly	0.190866	0.010***
L9 Blockchain	-1.106861	0.392
L10 Close Bitcoin Price weekly	0.017657	0.811
L10 Blockchain	-0.105959	0.936
L11 Close Bitcoin Price weekly	-0.106923	0.152
L11 Blockchain	-2.113955	0.106
L12 Close Bitcoin Price weekly	-0.214754	0.005***
L12 Blockchain	0.124947	0.923
L13 Close Bitcoin Price weekly	-0.031936	0.678
L13 Blockchain	-1.075367	0.455

$^{*}p < 0.1;^{**}p < 0.05;^{***}p < 0.01$

Table A10: VAR estimates of effect of Bitcoin weekly price on Blockchain Google Trends

Explanatory Variable	Dependent Variable	p-value
const	0.574770	0.015**
L1.Close Bitcoin Price weekly	0.009736	0.020**
L1.Blockchain	-0.271465	0.000***
L2.Close Bitcoin Price weekly	0.000497	0.907
L2.Blockchain	-0.210867	0.005***
L3.Close Bitcoin Price weekly	-0.001358	0.751
L3.Blockchain	-0.025842	0.729
L4.Close Bitcoin Price weekly	-0.006337	0.139
L4.Blockchain	-0.059126	0.433
L5.Close Bitcoin Price weekly	0.006872	0.113
L5.Blockchain	0.003858	0.959
L6.Close Bitcoin Price weekly	-0.002727	0.536
L6.Blockchain	0.091156	0.221
L7.Close Bitcoin Price weekly	-0.007947	0.071*
L7.Blockchain	0.171209	0.024**
L8.Close Bitcoin Price weekly	0.001251	0.776
L8.Blockchain	-0.067046	0.382
L9.Close Bitcoin Price weekly	0.005570	0.201
L9.Blockchain	-0.215107	0.005***
L10.Close Bitcoin Price weekly	0.005192	0.237
L10.Blockchain	-0.060043	0.441
L11.Close Bitcoin Price weekly	0.007382	0.096*
L11.Blockchain	-0.115528	0.137
L12.Close Bitcoin Price weekly	-0.001400	0.756
L12.Blockchain	-0.005860	0.939
L13.Close Bitcoin Price weekly	0.004841	0.290
L13.Blockchain	0.080439	0.347

$^{*}p < 0.1;^{**}p < 0.05;^{***}p < 0.01$

Appendix B Stationary time series graphs

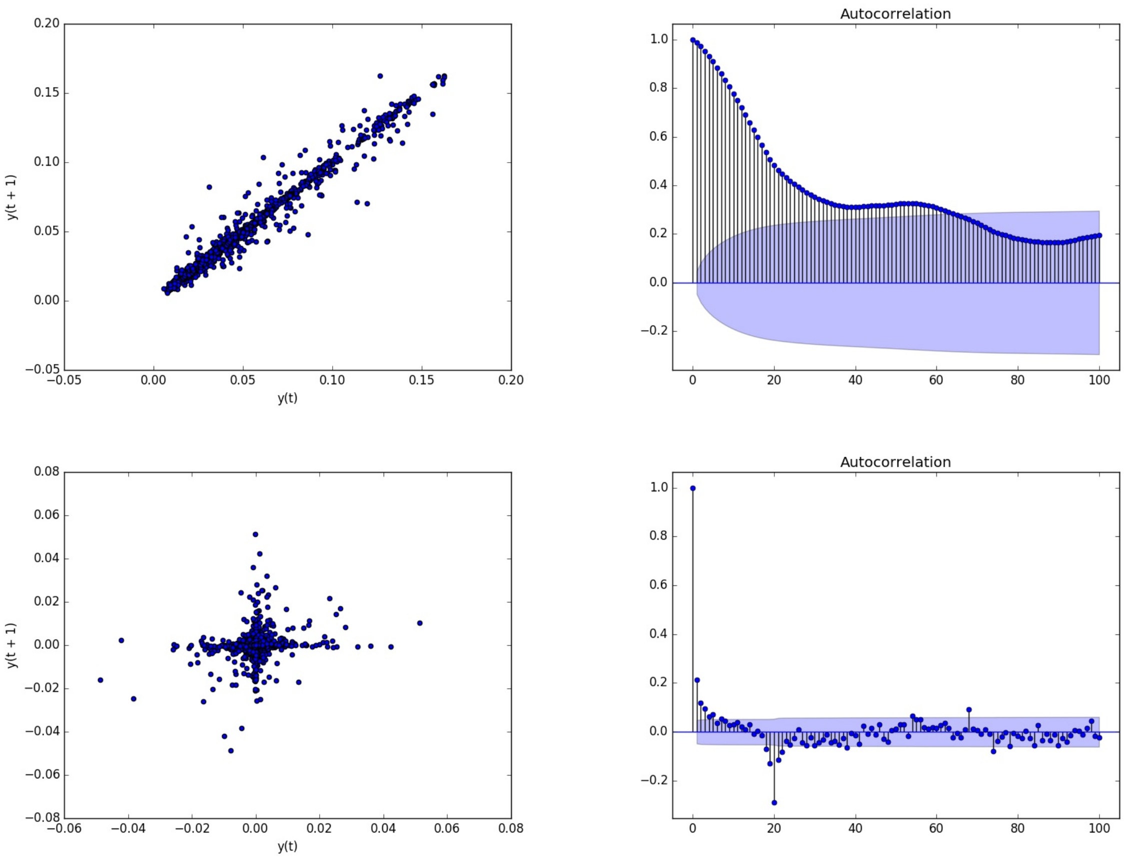

Figure B1: Proces of stationarity of Bitcoin price realized volatility. The two upper plots are plots of the Bitcoin price realized volatility before doing order 1 integration. The upper-left plot is the lag plot of this time series. The upper-right plot is the ACF plot of this time series. The lower two plots are plots of the Bitcoin price realized volatility after doing order 1 integration. The lower-left plot is the lag plot time series. The lower-right plot is the ACF plot in this time series.

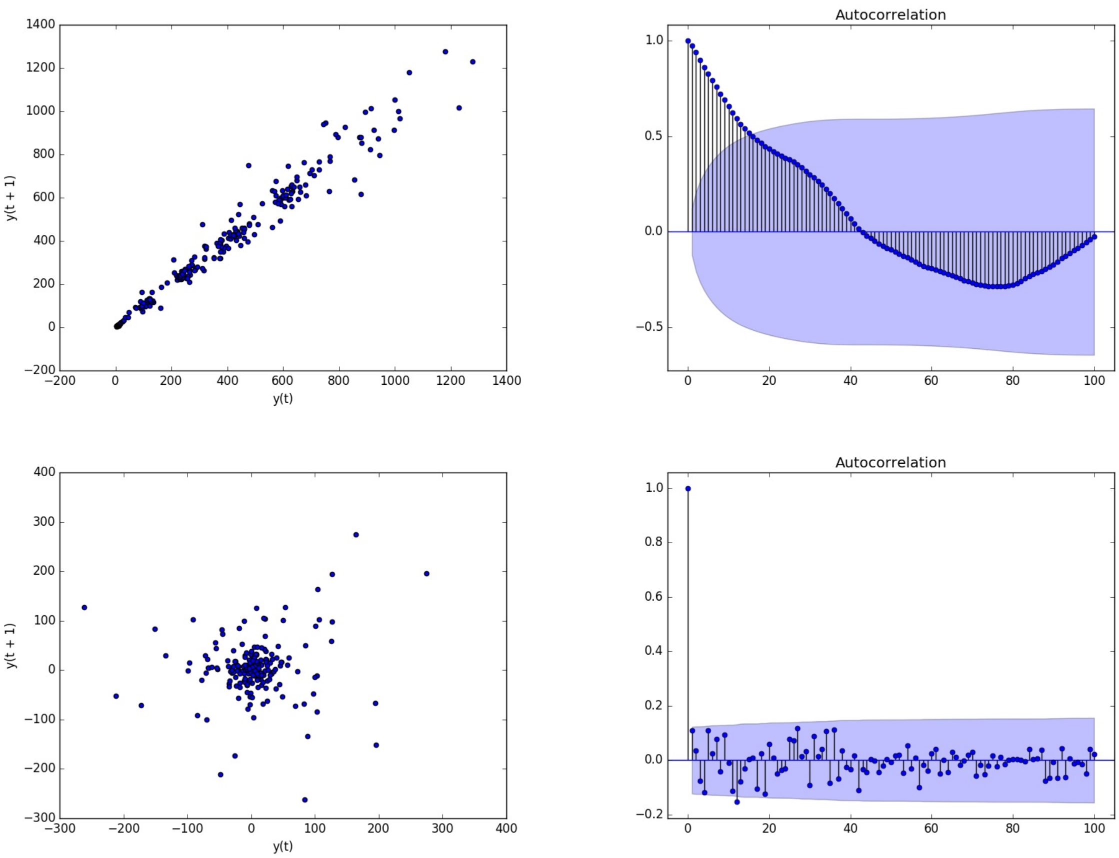

Figure B2: Proces of stationarity of Bitcoin weekly price. The two upper plots are plots of the Bitcoin weekly price before doing order 1 integration. The upper-left plot is the lag plot of this time series. The upper-right plot is the ACF plot of this time series. The lower two plots are plots of the Bitcoin weekly price after doing order 1 integration. The lower-left plot is the lag plot time series. The lower-right plot is the ACF plot in this time series.

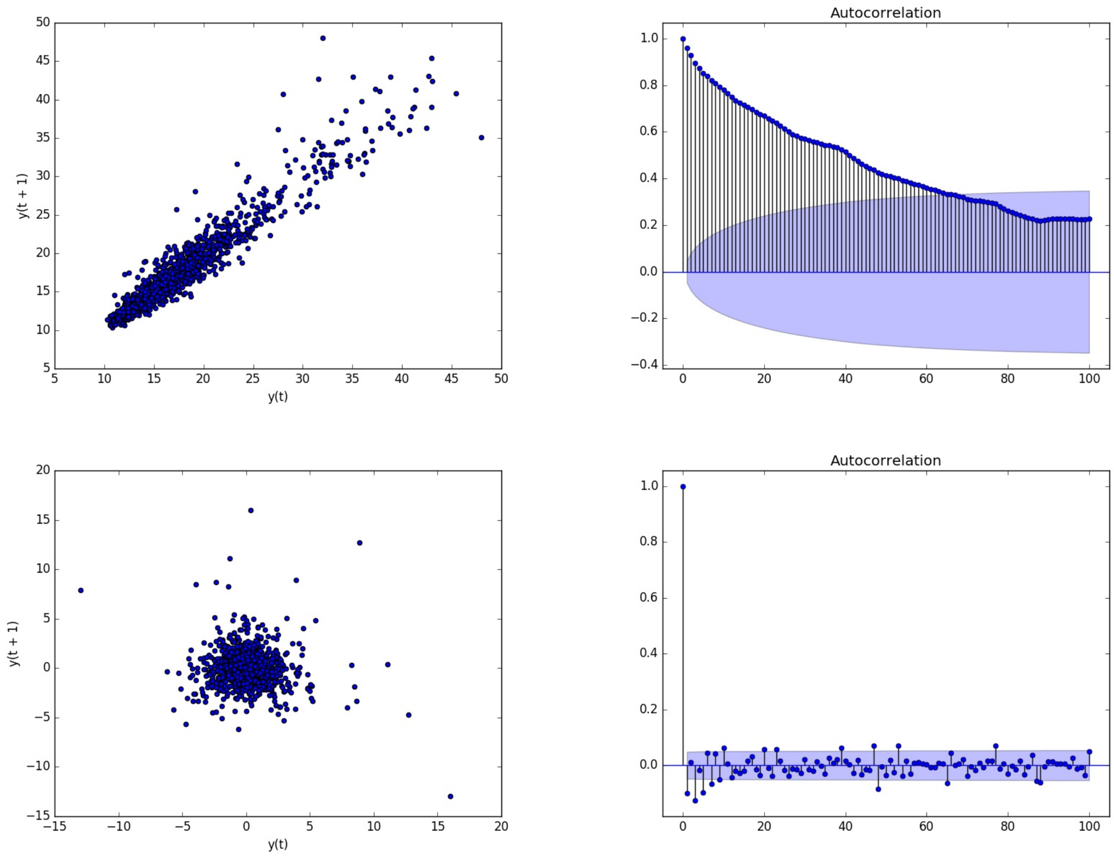

Figure B3: Proces of stationarity of S&P 500 VIX time series. The two upper plots are plots of the S&P 500 VIX time series before doing order 1 integration. The upper-left plot is the lag plot of this time series. The upper-right plot is the ACF plot of this time series. The lower two plots are plots of the S&P 500 VIX time series after doing order 1 integration. The lower-left plot is the lag plot time series. The lower-right plot is the ACF plot in this time series.

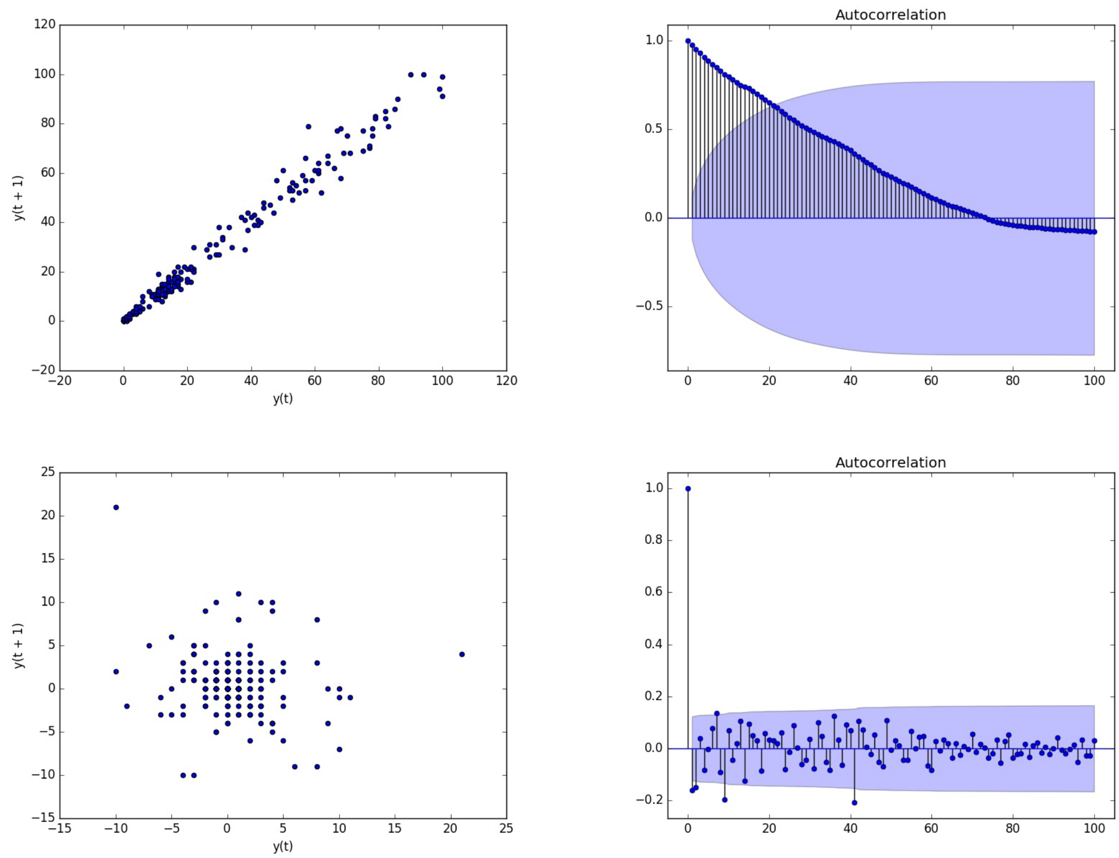

Figure B4: Proces of stationarity of Blockchain Google Trends time series. The two upper plots are plots of the Blockchain Google Trends time series before doing order 1 integration. The upper-left plot is the lag plot of this time series. The upper-right plot is the ACF plot of this time series. The lower two plots are plots of the Blockchain Google Trends time series after doing order 1 integration. The lower-left plot is the lag plot time series. The lower-right plot is the ACF plot in this time series.