The Curious Case of Bitcoin: Is Bitcoin volatility driven by online search?

by

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Abstract

The Bitcoin market has seen high periods of volatility since it was created in 2009. This paper seeks to forecast this volatility with online searches from Google Trends and Twitter. Google was chosen because of its high level of influence online and publicly available data. Twitter was chosen because social media's effects on financial asset prices are less well known. Granger causality tests on vector autoregressive models show that Google Trends has forecasting power on the realized volatility of Bitcoin. This Granger causality is bidirectional. Granger causality tests show that Twitter does not have forecasting power on the realized volatility of Bitcoin, but that volatility of Bitcoin does forecast future volume on Twitter.

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1 Introduction

Bitcoin was one of the most searched for terms on Google in 2013. It is an asset that has generated much media attention in the past year, and is highly volatile. What is driving its price changes? Unlike a traditional financial asset, there are relatively few measurable fundamentals like cash flow, dividends etc., that the value can be tied to. In the absence of those signals, I find other proxies for general market interest in Bitcoin, and use them to forecast future volatility.

I am interested in finding proxies for market interest in Bitcoin that can help forecast future volatility. Internet search data can describe the interest of individuals (Choi and Varian, 2009). This paper examines the relationship between Bitcoin, Google Trends and Twitter. Specifically, can past searches on Google Trends or tweets containing the word "Bitcoin" predict future periods of volatility? Following the work of Dimpfl and Jank (2011), I examine the relationship between Google Trends and the realized volatility of Bitcoin. While Dimpfl and Jank's study focused on aggregate stock indices, I look at Bitcoin as an individual asset. Google Trends is a good measure of market interest due to its high market share and influence online, and I use tweets because I want to know if social media can be used as a predictor for changes in the volatility of financial assets.

I use a Vector Autoregression (VAR) model is used to test the relationship between changes in realized volatility of Bitcoin and changes in Google Trends. I then employ the Granger causality methodology for testing the joint significance of these results. There is a statistically significant relationship between changes in Google Trends and changes in the realized volatility of Bitcoin. This Granger causality is bidirectional; changes in realized volatility have an impact on future Google Trends.

Tweets are not a statistically significant predictor of future realized volatility, however, realized volatility is a significant predictor of future tweet volume including the term "bitcoin". This implies that Google Trends is a better predictor of future volatility of Bitcoin than Twitter.

Granger causality shows that a variable x has power in forecasting a second variable, y. The potential ability to forecast future volatility could have significant impact for retail investors. In finance, volatility is used as a measure of risk. Bitcoin is no doubt a risky asset; its volatility is considerable. If investors and speculators can forecast some of that risk with increased certainty, they can make better informed decisions. Additionally, information about future volatility can have impacts on options and futures markets. The market for these kinds of derivatives is limited for Bitcoin today, but if the market continues to expand, those kinds of exchanges could become more prevalent.

Understanding and forecasting the volatility of Bitcoin could have importance to regulators, governments and the general public. If a government were to look at Bitcoin as a serious cash substitute, one area of concern would be its volatility. Money is in part a store of value; if the value of this money is volatile, agents will be interested in the ability to forecast it. Most central banks employ inflation targeting as their main tool in monetary policy, and changes in the money supply help to accomplish these targets. Bitcoin's supply is completely fixed, and grows at a fixed rate, meaning a "Bitcoin central bank" would not be able to affect changes in the supply even if it were advantageous from a policy perspective. This limits the ability to induce liquidity and causes high volatility as demand shocks hit the market.

Previous papers have established the relationship between Google Trends, Twitter and the stock market. The value of this exercise is that it looks at a specific asset that we do not know much about, and show that its volatility can be at least partially forecasted. Additionally, I look at both Google Trends and Twitter within the same framework. Previous studies have looked at either Google or Twitter, but not both, and not using the same method.

2 Literature Review

The literature on Bitcoin within an economic framework is non existent. However, there are several studies that look at the relationship between financial assets and online proxies for market interest. Dimpfl and Jank, whose study this paper is roughly based off of, find that Google Trends are a significant predictor of future volatility in stock markets. Specifically, they looked at indexes (for example the S&P 500) and tested how Google Trends predicted future periods of volatility. Their analysis showed that both variables Granger-caused one another, consistent with my results.

Bollen et al. (2011) identified that including public mood dimensions can improve stock market forecasts. They took a sample of tweets within the timeframe of interest, identified the "mood" of the tweets, and found that emotional days on Twitter predicted negative returns in the stock market. Notably, they did not look at tweets only containing keywords, but looked at a random subsample of all tweets. This differs from my analysis; I am only looking at tweets that contain the word "bitcoin", and I am not identifying mood. Their analysis helped confirm that tweets could have predictive value in markets.

Dergiades et al. (2013) looked at the Greek-German government bond yield differential, and found that social media discussion and related searches "provide significant short-run information primarily for the Greek-German government bond yield differential even when other control variables are accounted for".

These are again consistent with my results.

Finally, Choi and Varian (2012) showed that search engine data can be used to forecast economic variables like unemployment claims, auto sales, and consumer confidence. They find that autoregressive models that include Google Trends data “outperform” models without them by 5-20%. My model shows that including past values of Google Trends is a better predictor of future market volatility than future market volatility alone.

It seems that Google Trends and Twitter have some predictive power when it comes to economic variables. This paper further adds to this literature, and shows that Google Trends is a useful predictor in the market for Bitcoin, while Twitter is not. The literature does not show any contributions specific to the Bitcoin market with this kind of exercise.

3 Background

Bitcoin is a cryptocurrency that was introduced in 2009. It is designed to be accepted all over the world as a replacement for cash, credit card and bank wire transactions. Bitcoin has seen rapid growth in the past few years; in 2013, the price grew by 5857%. Bitcoin is unique because it does not use financial intermediaries or banks, and it is completely unregulated. An individual that wants to send a Bitcoin (or division thereof; Bitcoins are divisible by up to 8 decimal places) to another individual simply has to have their unique address, a cryptographic number unique to each individual.

The Bitcoin marketplace can be reduced to three main actors. The two transactors who come together to trade Bitcoins, and a miner. Miners add transactions between the traders to the public ledger of past transactions, and thus “confirm” them. A good analogy for a miner would be an escrow account; I can send Bitcoins to another user, but they haven’t truly switched hands until they are confirmed by a miner. The ledger is then public, and helps to prevent double spending.

Another important function of miners is the creation of new coins. Traditional fiat money is printed by central banks, whereas Bitcoins are in some sense “discovered” by miners using cryptography and computing power. The mechanics of mining are fascinating, but for the purposes of this paper it is sufficient to say that the rate of difficulty in discovering these coins increases over time, and the reward for discovering them decreases. This provides the supply shown in Figure 1, which increases over time at a decreasing rate.

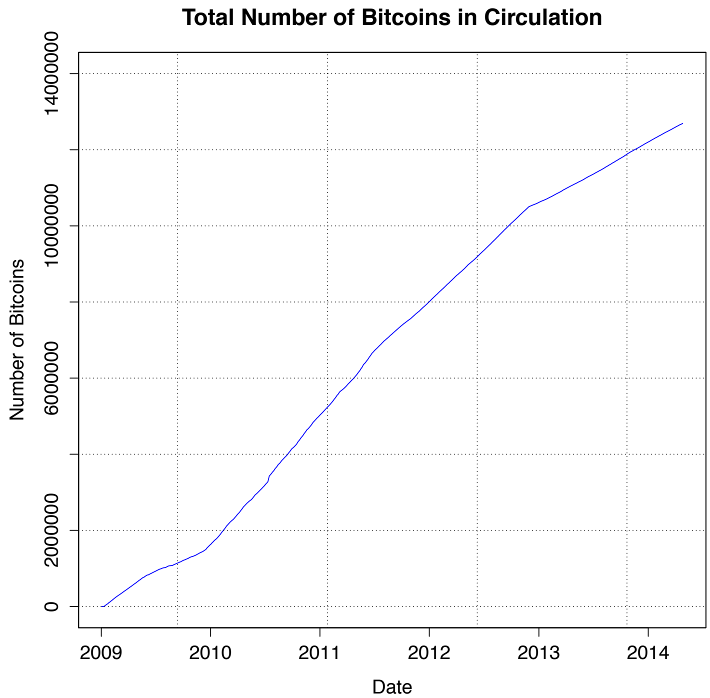


Figure 1: Bitcoin Supply

The term "mining" is not coincidental; mining coins is similar to mining a precious metal like gold. The more that is mined, the harder it is to mine the next unit of gold, or in this case, Bitcoin. The marginal cost of mining the next coin increases over time, while the marginal benefit decreases; miners receive less Bitcoins on the margin for each new block added to the chain. On average, the number of Bitcoins created per block halves every 4 years. In 2140, the 21 millionth Bitcoin will be mined, and the supply will be set.

The system and properties described above have important implications for volatility. If agents are forward-looking, the supply is known perfectly in advance. With that simple assumption, I can say with a degree of certainty that any volatility in the price of Bitcoin is driven purely by demand shocks. This provides some intuition as to why Google Trends or Twitter may impact volatility; if online searches are proxies for market interest, then perhaps changes in online searches are representative of demand shocks.

4 Data and Descriptive Statistics

Google Trends is a feature that allows users to see how often a term of interest is being searched for in relation to total searches. It is intended to show a term's popularity over time. Users can go to www.google.ca/trends and search for any word or term over a specified timeframe. Google does not provide raw search data, however, it provides a normalized series. The highest value of search during the period of interest is indexed to an arbitrary value of 100, and every other observation is relative to 100. For example, if one observation in the series is 80, this implies that the search level for that observation was roughly 80% of the highest during the series.

I use weekly Google Trends data from January 2011 to January 2014 with the keyword “Bitcoin”. This captures all searches that contain the term; ie. one could search for “Bitcoin price”, and it would be captured in this series. As per Dimpfl and Jank (2011), one advantage of using Google data is that it has a large market share all over the world, which allows me to make stronger inferences.

The relationship between Google Trends and Bitcoin became interesting to me when I saw the high degree of correlation ($\rho_{B,G} = 0.844$, where B is Bitcoin and G is Google Trends) between the two series. See Figure 2 for a graphical representation of this relationship.

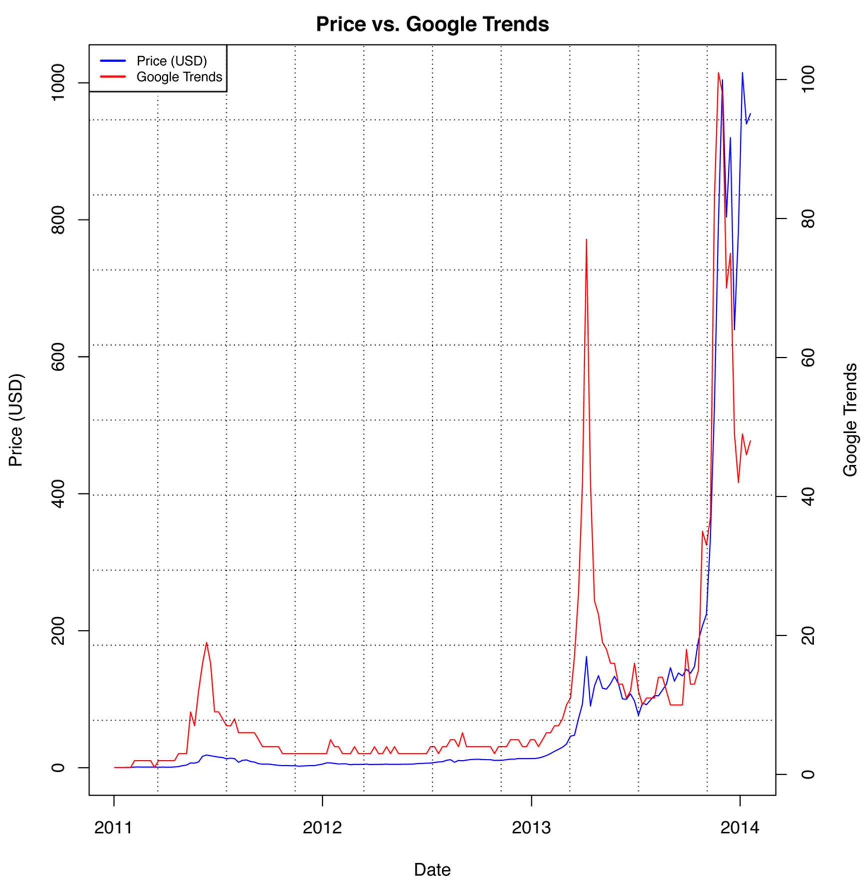


Figure 2: Price vs. Google Trends

A novel contribution of this paper is testing the influence of Twitter as well as Google. I use all tweets for the period of January 2011 to January 2014 with the keyword "Bitcoin"; this method and time period is identical to my methodology for Google, which allows me to compare the influence of both measures.

The relationship between the price of Bitcoin and tweets is similar to that of Google, as per Figure 3. However, I will show that while the overall trend looks similar, the relationship is not at all the same. The correlation between the series is actually higher for Twitter and Bitcoin, with $\rho_{B,T} = 0.940$, where T is tweets.

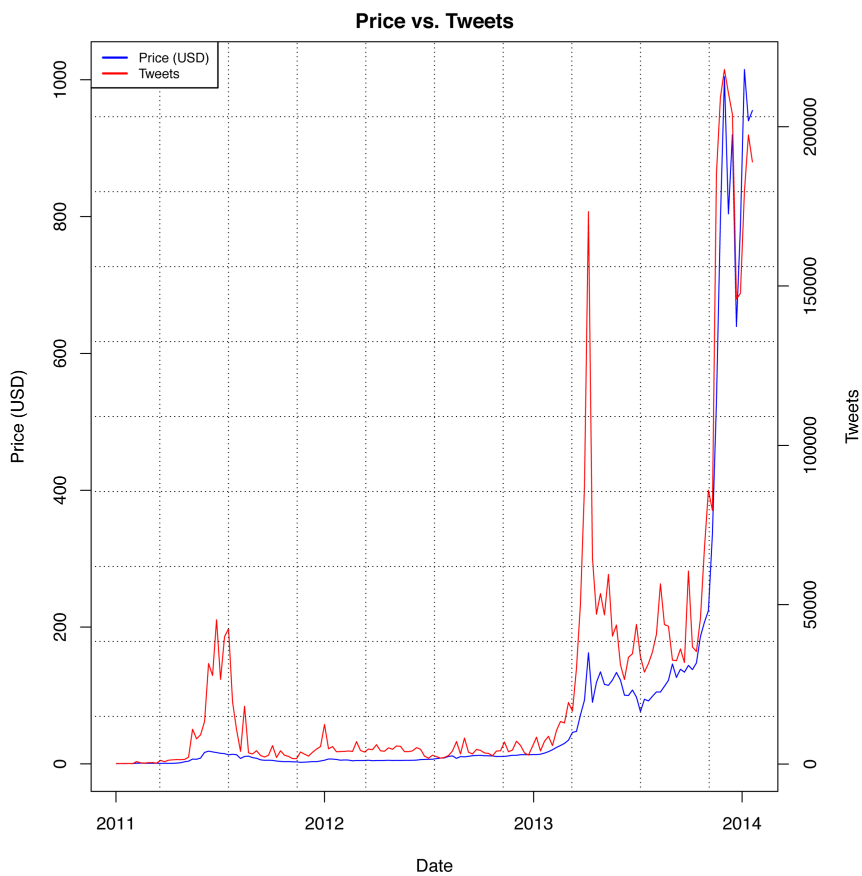


Figure 3: Price vs. Tweets

To perform this analysis on Bitcoin, I created a realized volatility series of returns from January 2011 to January 2014. Data were obtained from Quandl, a search engine for numerical data. The series was made through a method consistent with previous literature. Specifically, this method was introduced by Andersen et al. (2003). The method is:

$$RV_t = \sqrt{\sum_{i=1}^{n} r_{t,i}^2}$$

where RV_t is realized volatility at time t, $r^2_{t,i}$ is the sum of squared returns during interval j. I created the series as weekly realized volatility in order to be consistent with Google Trends data; daily Google data is not available. Summary statistics for the price of Bitcoin, Google Trends, tweets, and realized volatility can be found in Table 1.

Table 1: Summary Statistics for Data
January 2011 - January 2014

	Price (USD)	*Google Trends*	*Tweets*	*Realized Volatility*
Observations	158.00	158.00	158.00	158.00
Minimum	0.30	1.00	112.00	0.01
Maximum	1015.00	101.00	217951.00	0.74
1. Quartile	4.94	3.00	3161.75	0.05
3. Quartile	86.62	11.00	32255.75	0.17
Mean	75.47	11.18	24985.68	0.13
Median	10.87	4.00	5295.50	0.09
Sum	11924.62	1767.00	3947738.00	20.20
Variance	33376.72	299.68	1971520835.01	0.01
St Dev	182.69	17.31	44401.81	0.11
Skewness	3.75	3.29	2.91	2.09
Kurtosis	13.97	11.38	8.36	5.91

The price of Bitcoin is clearly volatile, as per Table 1. The 3rd quartile of the price is only 86.62, while the maximum is 1015.00. Clearly, the tail of the distribution is quite large, which is reflected in the variance and standard deviation of the price.

Realized volatility follows close to a log-normal distribution, and a Jarque-Bera test of normality cannot be rejected. This is a desirable property for realized volatility series. According to Andersen et al. (2003), "vector autoregressive volatility forecast, coupled with a parametric lognormal-normal mixture distribution implied by the theoretically and empirically grounded assumption of normally distributed standardized returns, produces well-calibrated density forecasts of future returns, and correspondingly accurate quantile predictions". This implies that for correct forecasting, realized volatilities should be normally distributed. I also test for autocorrelation among the log of realized volatilities; it displays decaying autocorrelation over time.

5 Methodology and Models

The econometric methodology I use was introduced by Toda and Yamamoto (1995). They find that if any of the data being tested are non-stationary, then we can model in levels (or log-levels) with the degree of integration added in as an extra lag. We then remove that extra lag when performing Wald tests, and the test statistic will follow its usual asymptotic χ^2 distribution under the null. The extra lag is there to ensure the statistic's asymptotic properties hold. This also holds when the data are cointegrated, which, in this case they are not. This is in contrast to normal practice, which involves running the data in their first differences.

Here I establish the relationship between realized volatility, Google Trends, and tweets. Through Akaike information criterion (AIC), I determined that an order three vector autoregression, VAR(3), was appropriate for the Google model. I added three extra lags to account for serial correlation in the residuals. With 6 lags, a Portmanteau test of no serial correlation in the residuals could not be rejected.

An Augmented Dickey-Fuller test showed that all the applicable series (log realized volatility, log Google Trends, and log tweets) had a unit root of order 1 (Dickey and Fuller, 1979). This means that the data are non-stationary, so I added an extra lag in each model to employ the Toda and Yamamoto approach, making a total of 7 lags.

First order integration is common in time series models. If data being tested are non-stationary, there is a significant risk of finding a spurious relationship among the variables. Spurious relationships occur when one variable is hypothesized to influence another, but there is a third compounding variable that influences both. Having taken care of the stationarity problem, I can now proceed.

For the tweet model, AIC of two was appropriate. There was no serial correlation in the residuals, so I added the degree of integration in and used three lags in total for this model.

The models are specified as:

$$log(RV_t) = \alpha_1 + \sum_{j=1}^{7} \gamma_{1,j} log(RV_{t-j}) + \sum_{j=1}^{7} \beta_{1,j} log(GT_{t-j}) + \varepsilon_{1,t} \tag{1}$$

$$log(GT_t) = \alpha_2 + \sum_{j=1}^{7} \delta_{1,j} log(RV_{t-j}) + \sum_{j=1}^{7} \phi_{1,j} log(GT_{t-j}) + \varepsilon_{2,t} \tag{2}$$

$$log(RV_t) = \mu_1 + \sum_{j=1}^{3} \psi_{1,j} log(RV_{t-j}) + \sum_{j=1}^{3} \omega_{1,j} log(TW_{t-j}) + \nu_{1,t} \tag{3}$$

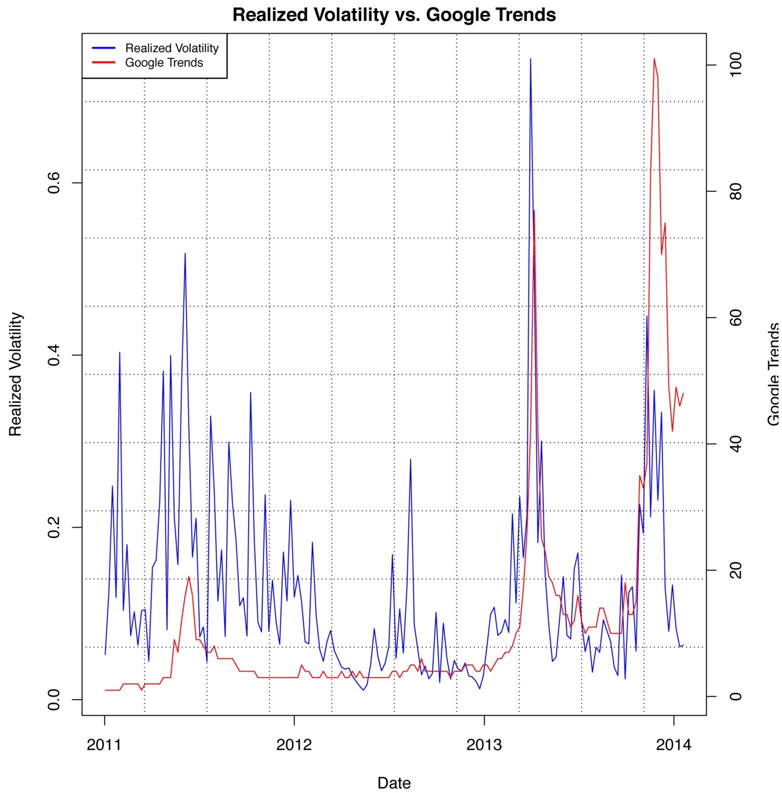
$$log(TW_t) = \mu_2 + \sum_{j=1}^{3} \theta_{1,j} log(RV_{t-j}) + \sum_{j=1}^{3} \eta_{1,j} log(TW_{t-j}) + \nu_{2,t} \tag{4}$$

where RV_t is realized volatility at time t, GT_t is Google Trends at time t, and TW_t is tweets at time t. Results for the regression models can be found in the Results section below.

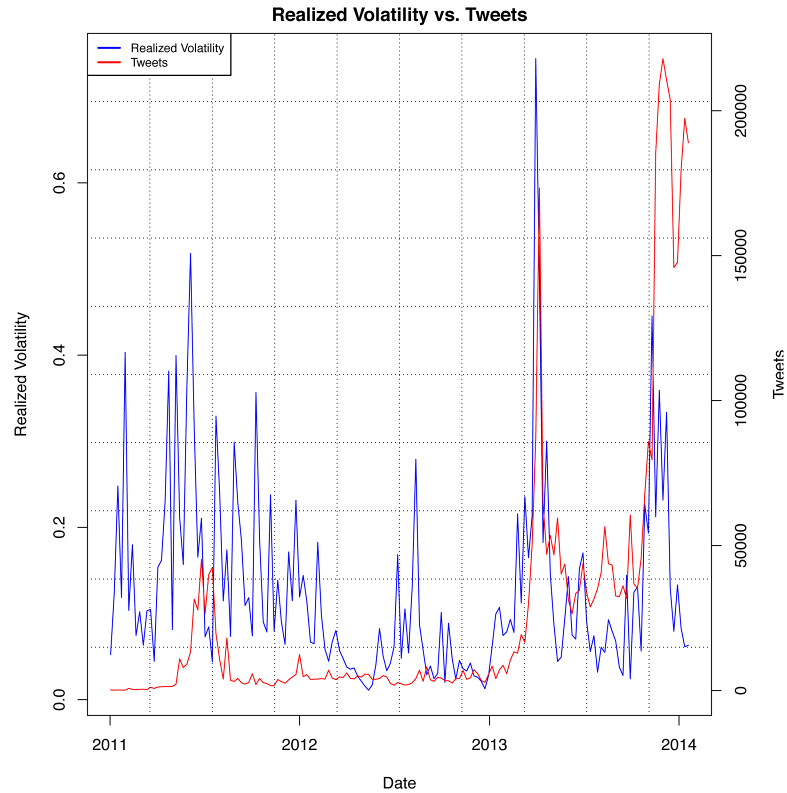
I use Granger causality to test the joint significance of the coefficients. Again, the 7th lag in Models 1 & 2, or 3rd in Models 3 & 4 comes out for the Wald test. This gives the Wald test statistic an asymptotic

χ^2 distribution with 6 and 2 degrees of freedom, respectively.

Figures 4 & 5 show the relationship between the variables of interest in the models, and their relationships in logarithms, which are what is actually being tested.

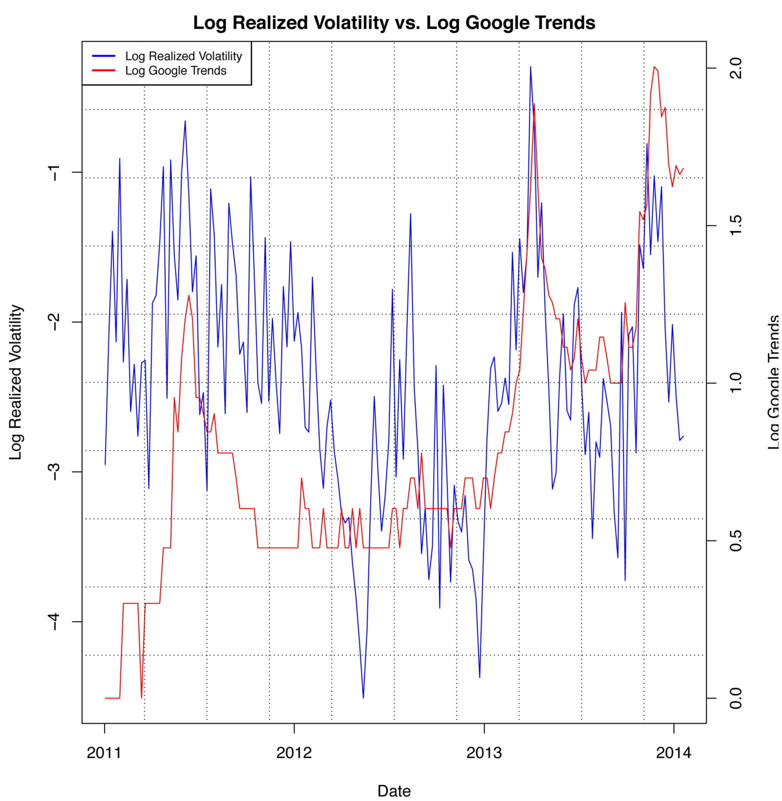


(a) Realized volatility vs. Google Trends

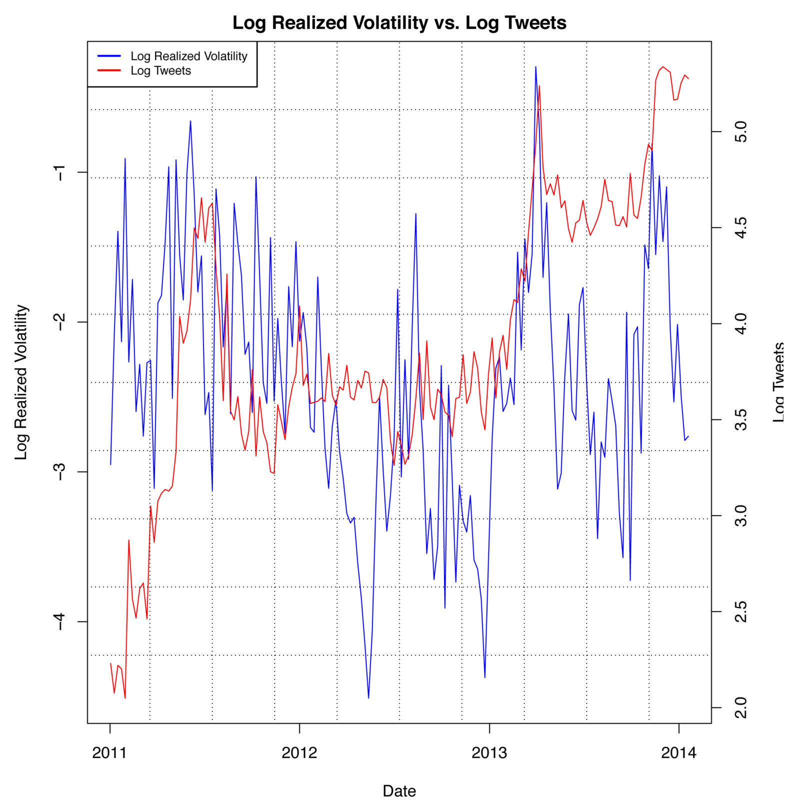


(b) Realized volatility vs. Tweets

Figure 4: Realized volatility vs. search parameters



(a) Log realized volatility vs. Log Google Trends



(b) Log realized volatility vs. Log Tweets

Figure 5: Log realized volatility vs. log search parameters

6 Results & Discussion

6.1 Realized Volatility & Google Trends

Table 2: VAR Estimates of the Effect of Google Trends on Realized Volatility of Bitcoin

Explanatory Variable	**Dependent Variable: Log Realized Volatility**
Realized Volatility Lag 1	0.352***
	(0.087)
Realized Volatility Lag 2	0.223**
	(0.093)
Realized Volatility Lag 3	0.062
	(0.097)
Realized Volatility Lag 4	−0.005
	(0.099)
Realized Volatility Lag 5	0.194*
	(0.100)
Realized Volatility Lag 6	−0.035
	(0.102)
Realized Volatility Lag 7	−0.032
	(0.093)
Google Trends Lag 1	0.360
	(0.225)
Google Trends Lag 2	0.238
	(0.314)
Google Trends Lag 3	−0.346
	(0.306)
Google Trends Lag 4	−0.355
	(0.305)
Google Trends Lag 5	−0.278
	(0.296)
Google Trends Lag 6	0.365
	(0.278)
Google Trends Lag 7	0.032
	(0.203)
Constant	−0.635**
	(0.281)
Observations	153
R^2	0.52
Residual Std. Error (dof = 138)	0.602

*p<0.1; **p<0.05; ***p<0.01

[1] Notes: Standard errors are in parentheses. Data are from Quandl and Google, from January 2011 to January 2014. All regressors modelled have been included in this table. All regressors are in logarithms, as is the dependent variable.

Table 2 shows the VAR results between the log of Google Trends and the log of realized volatility of Bitcoin. All coefficients should be interpreted as a standard log-log model; for example, a 1% increase in realized volatility at $t-1$ increases realized volatility at time t by 0.352%. The lack of individual significance on the Google Trends lags should not be of large concern since I am testing the joint significance through Granger causality.

The extra lag that was added in for the degree of integration comes out in the Wald Test for Granger causality. This leads to my test statistic being χ^2 distributed with 6 degrees of freedom. The result of the Granger causality test is in Table 3 below.

Table 3: Log Google Trends on log realized volatility Granger causality test

	Log Realized Volatility
χ^2	14.2
DOF	6
Asymptotic P-Value	0.027

Google Trends is said to Granger-cause realized volatility if realized volatility can be better predicted by using both lagged values of itself and Google Trends compared to just using lagged values of itself. Table 3 shows that I reject the null hypothesis that Google Trends does not Granger-cause realized volatility at the 10% and 5% significance levels.

This result could be of use to governments, regulators and market participants. Financial economic theory tells us that investors care about risk and return, where risk is generally thought of as variability in returns. Any information that can help investors become more informed about either of these metrics could be of great value. Knowledge about volatility could also provide potential buyers opportunities to trade derivative securities such as options and futures, as a hedge. Understanding and being able to forecast volatility better could have implications for regulators as well, as mentioned in section 1.

Table 4 shows the effects of the realized volatility of Bitcoin on Google Trends. The relationship here is much stronger; ceteris paribus realized volatility predicts Google Trends better than Google Trends predicts realized volatility. This is not surprising. There are factors other than Google searches that have an effect on Bitcoin volatility; I mentioned earlier Google is simply a proxy for market interest. However, there are likely few factors that affect Bitcoin Google searches aside from realized volatility. This is evident in my coefficient significance, and also my R^2 values in Table 2 and Table 4.

Table 4: VAR Estimates of the Effect of Realized Volatility of Bitcoin on Google Trends

Explanatory Variable	**Dependent Variable: Log Google Trends**
Realized Volatility Lag 1	0.119^{***}
	(0.033)
Realized Volatility Lag 2	-0.108^{***}
	(0.036)
Realized Volatility Lag 3	0.097^{***}
	(0.037)
Realized Volatility Lag 4	-0.092^{**}
	(0.038)
Realized Volatility Lag 5	0.094^{**}
	(0.038)
Realized Volatility Lag 6	-0.068^{*}
	(0.039)
Realized Volatility Lag 7	-0.052
	(0.035)
Google Trends Lag 1	0.997^{***}
	(0.086)
Google Trends Lag 2	-0.108
	(0.120)
Google Trends Lag 3	0.183
	(0.117)
Google Trends Lag 4	-0.140
	(0.117)
Google Trends Lag 5	-0.018
	(0.113)
Google Trends Lag 6	0.039
	(0.106)
Google Trends Lag 7	0.029
	(0.078)
Constant	0.035
	(0.108)
Observations	153
R^2	0.95
Residual Std. Error (dof = 138)	0.230

*p<0.1; **p<0.05; ***p<0.01

[1] Notes: Standard errors are in parentheses. Data are from Quandl and Google, from January 2011 to January 2014. All regressors modelled have been included in this table. All regressors are in logarithms, as is the dependent variable.

Granger causality results are in Table 5 below; here I reject the null at all standard significance levels. Again, this result is consistent with the basic assumption that big changes in volatility will lead to more searches.

Table 5: Log realized volatility on log Google Trends Granger causality test

	Log Google Trends
χ^2	36.3
DOF	6
Asymptotic P-Value	0.000

6.2 Realized Volatility & Tweets

The other variable I hypothesized affecting realized volatility of Bitcoin was tweets. Tweets containing the term "Bitcoin" could be another identifier of market interest. In theory, tweets in period $t-1$ could be a predictor of volatility in period t, but this does not end up being the case. VAR results are in Table 6 below.

Table 6: VAR Estimates of the Effect of Tweets on Realized Volatility

Explanatory Variable	**Dependent Variable: Log Realized Volatility**
Realized Volatility Lag 1	0.399^{***}
	(0.080)
Realized Volatility Lag 2	0.295^{***}
	(0.085)
Realized Volatility Lag 3	0.047
	(0.082)
Tweets Lag 1	0.050
	(0.112)
Tweets Lag 2	0.140
	(0.128)
Tweets Lag 3	-0.191^{*}
	(0.108)
Constant	-0.631^{*}
	(0.365)
Observations	157
R^2	0.47
Residual Std. Error (dof = 150)	0.616

*p<0.1; **p<0.05; ***p<0.01

[1] Notes: Standard errors are in parentheses. Bitcoin data are from Quandl. Twitter data graciously provided by Tony Tam from Bitcoin Pulse, from January 2011 to January 2014. All regressors modelled have been included in this table. All regressors are in logarithms, as is the dependent variable.

Tweets don't have any significant positive effects on realized volatility, and this is captured in the Granger causality test. Jointly, the coefficients are not statistically different from zero, so I fail to reject the null hypothesis that tweets do not Granger-cause realized volatility, as per Table 7 below.

Table 7: Log tweets on log realized volatility Granger causality test

	Log Realized Volatility
χ^2	0.46
DOF	2
Asymptotic P-Value	0.8

This perhaps highlights a difference between every day uses of Google and Twitter. Google is used for search and informational purposes; users go there to research products before purchasing them. Internet search data can describe the interest of individuals (Choi and Varian, 2009). However, Twitter is a microblogging website designed for users to share opinions, pictures, and short posts. It makes sense intuitively, then, that Twitter would not have predictive power in markets like Bitcoin.

If Twitter is more reactive, then Bitcoin volatility should have some predictive power for tweets. If Twitter is a place people go to discuss events mostly after they have happened, then periods of high volatility should spark more discussion. The VAR results for the effects of Realized Volatility on tweets is in Table 8 below.

Table 8: VAR Estimates of the Effect of Realized Volatility on Tweets

Explanatory Variable	**Dependent Variable: Log Tweets**
Realized Volatility Lag 1	0.166^{***}
	(0.058)
Realized Volatility Lag 2	-0.139^{**}
	(0.061)
Realized Volatility Lag 3	0.093
	(0.059)
Tweets Lag 1	0.644^{***}
	(0.081)
Tweets Lag 2	0.207^{**}
	(0.092)
Tweets Lag 3	0.101
	(0.078)
Constant	0.792^{***}
	(0.263)
Observations	157
R^2	0.92
Residual Std. Error	0.444
(df = 150)	

*p<0.1; **p<0.05; ***p<0.01

[1] Notes: Standard errors are in parentheses. Bitcoin data are from Quandl. Twitter data graciously provided by Tony Tam from Bitcoin Pulse, from January 2011 to January 2014. All regressors modelled have been included in this table. All regressors are in logarithms, as is the dependent variable.

Table 9: Log realized volatility on log tweets Granger causality test

	Log Tweets
χ^2	9.8
DOF	2
Asymptotic P-Value	0.007

Here I reject the null hypothesis that realized volatility does not Granger-cause changes in tweets, indicating that realized volatility does have some predictive power there. This is similar to the effect of volatility on Google, but not as strong.

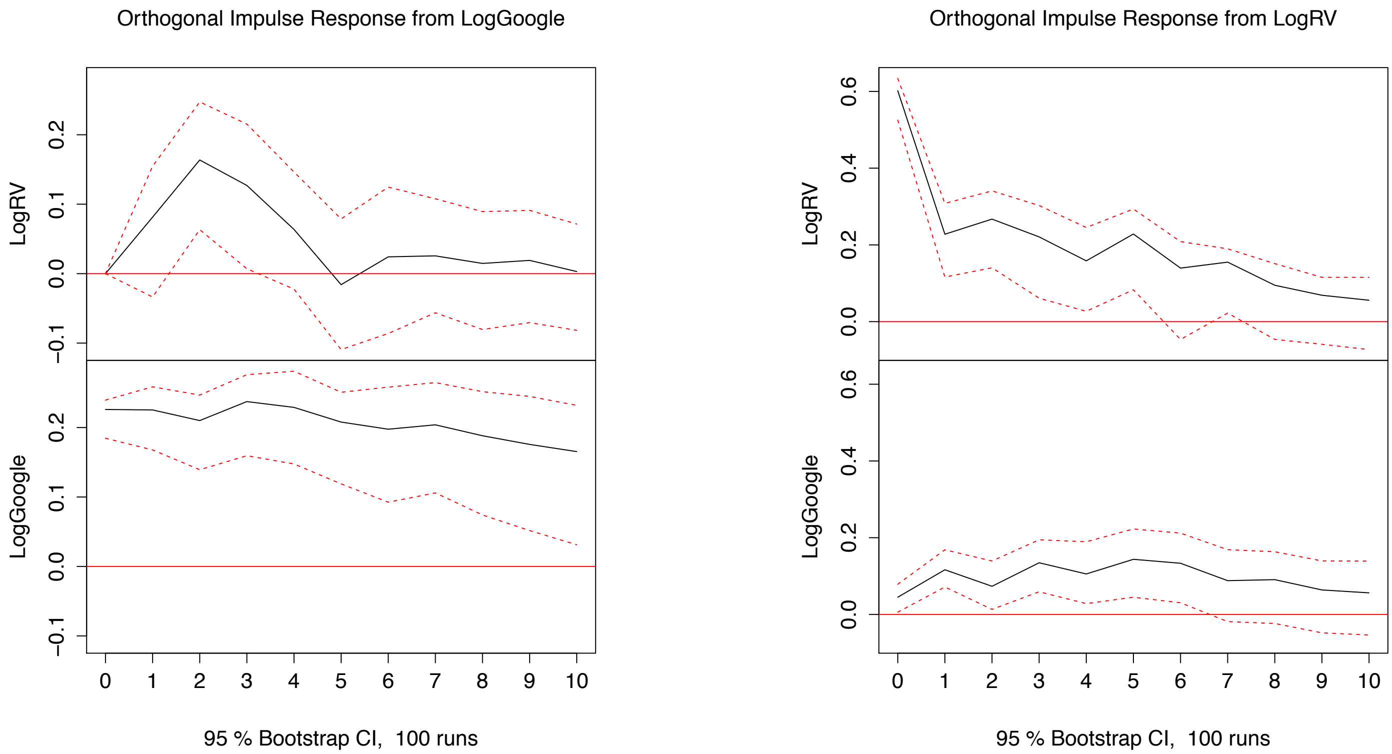
Based on all of the results I have presented in the four different models, I can conclude that Google Trends provides a better forecast of volatility, and volatility provides a better forecast of Google Trends that Twitter.

6.3 Further Analysis

Granger causality tests do not provide any information regarding the direction of the impact the variable of interest has on the dependent variable. This matters because I want to ensure that a positive change in Google Trends has a positive effect on realized volatility, not a negative one.

To check this, I use impulse response functions. Impulse response functions act as an exogenous shock to the error term of a VAR model; specifically a one standard deviation increase. Figure 6 shows the effects of increasing log Google Trends and log realized volatility by one standard deviation. Figure 7 shows the effects of increasing log tweets and log realized volatility by one standard deviation.

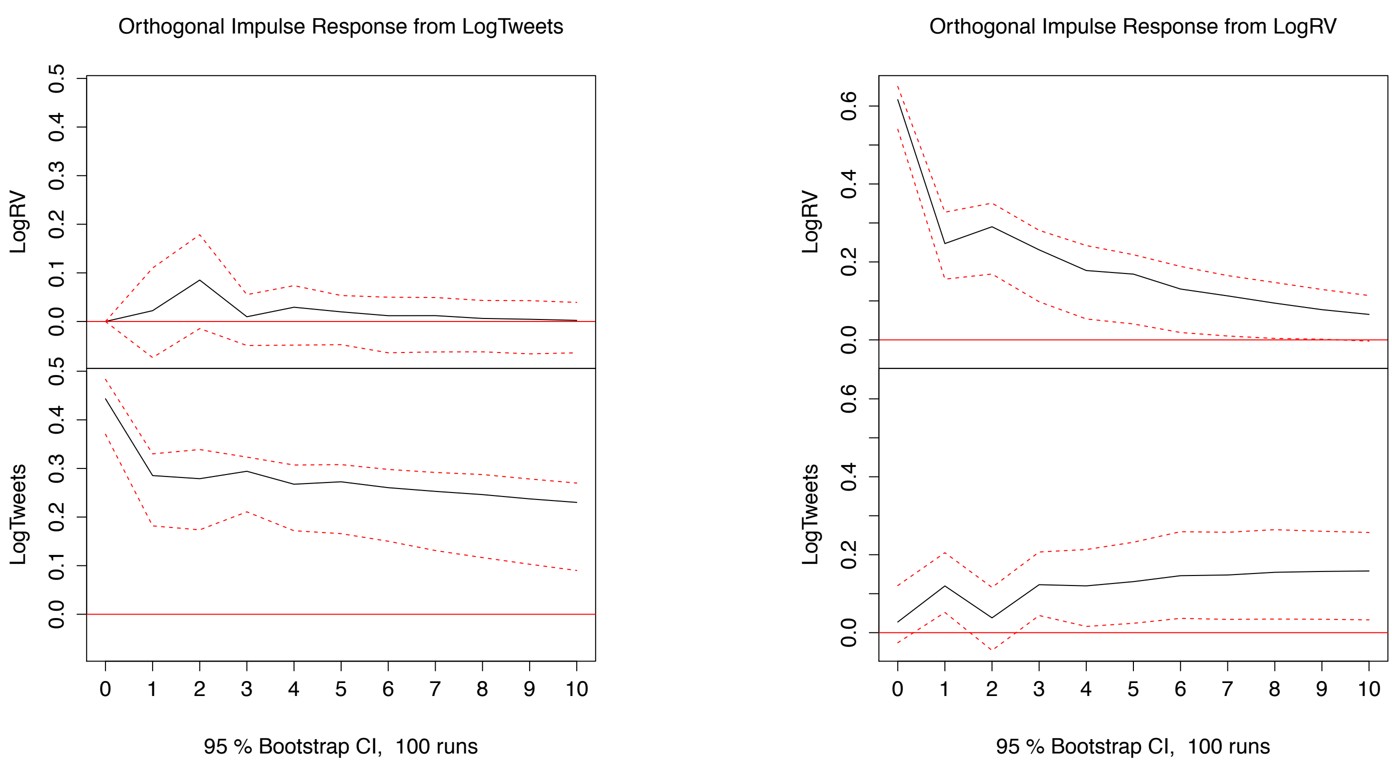
The direction of the response is consistent with my hypothesis. An increase in Google Trends has a positive impact on volatility, and an increase in volatility has a positive impact on Google Trends. The shocks have different effects on each variable. The x-axis on the impulse response functions represent the number of weeks since the shock, while the y-axis represents the magnitude of the response. This implies that shocks are more persistent among some variables than others. For example, a shock from Google Trends has a large positive effect on realized volatility, and the shock has a persistent effect for approximately five weeks.



(a) Increase in Google Trends

(b) Increase in realized volatility

Figure 6: Impulse response functions from Google Trends and realized volatility



(a) Increase in tweets

(b) Increase in realized volatility

Figure 7: Impulse response functions from tweets and realized volatility

Red lines are a 95% bootstrapped confidence interval

7 Conclusion

In this paper I showed the relationship between the volatility of Bitcoin and two different measures of online search. The VAR and Granger causality results shown in this paper indicate that changes in Google Trends have an effect on the realized volatility of Bitcoin. Changes in the volatility of Bitcoin also have an effect on Google searches for Bitcoin. This implies that Google Trends can be a useful tool for forecasting future periods of volatility in the market for Bitcoin. This result is consistent with past literature that looked at the effects of Google Trends on the stock market.

Twitter is not a good forecaster of future Bitcoin volatility. However, increases in volatility does forecast an increase in tweets about Bitcoin. The difference between the results for Google Trends and Twitter highlights the different ways that people use these services. Google is used for educational purposes, while Twitter is more reactionary.

I also showed that positive shocks to the explanatory variables of interest lead to a positive response from realized volatility, as shown in their impulse response functions. This is consistent with my hypothesis that increased searches should have a positive impact on volatility.

The information in this paper may be of interest to regulators, governments and Bitcoin market participants. Bitcoin has been proposed as a substitute for cash, credit card and bank transfer transactions. If agents can forecast volatility with a higher degree of certainty, they can make better informed decisions regarding purchasing coins, accepting them as a method of payment, or in the regulator's case, allowing them to be used and under what circumstances.

This study was limited to the data available on Bitcoin. If more firms start to accept Bitcoin as a method of payment, future work could look at the impact of additional firms on future volatility. Theoretically, as more firms accept Bitcoin, it should reduce volatility. The volatility that has occurred in the past few years could also be a natural progression as a new asset develops; perhaps volatility will decrease if Bitcoin becomes more mainstream.

There are many issues with Bitcoin as a payment and financial system; this paper looked at just one of them. Volatility of a currency is an undesirable property. From a financial asset perspective, these large swings are detrimental to the future of Bitcoin. Understanding how to better forecast this volatility has value to current and potential future users.

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A Normality Test

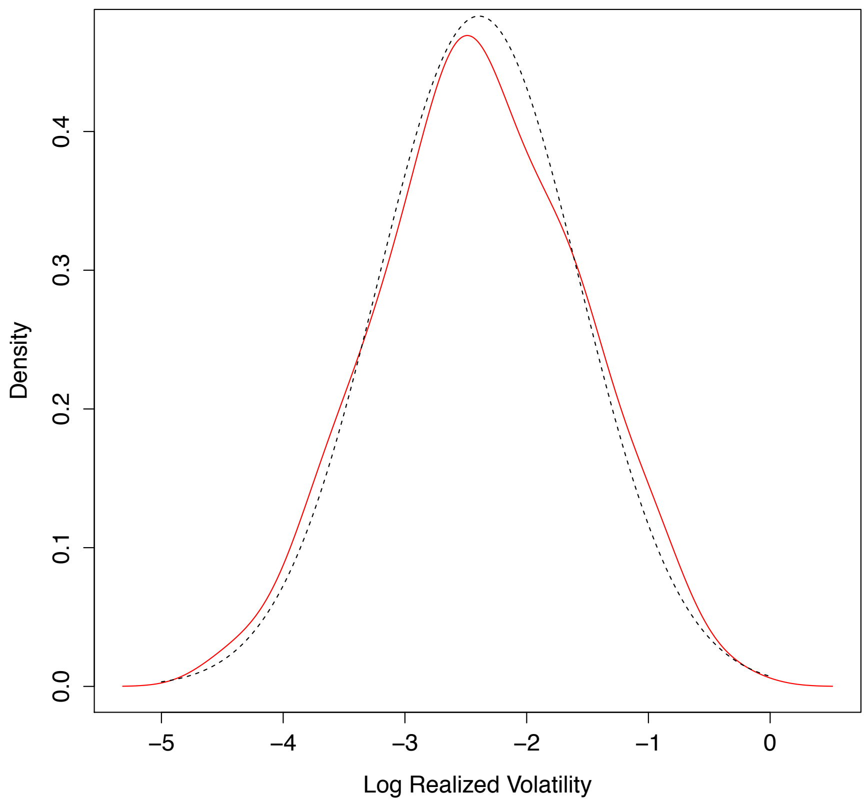


Figure 8: Cumulative density function of log realized volatility

The dotted line represents a normally distributed random variable. The red line represents the CDF of log realized volatility.

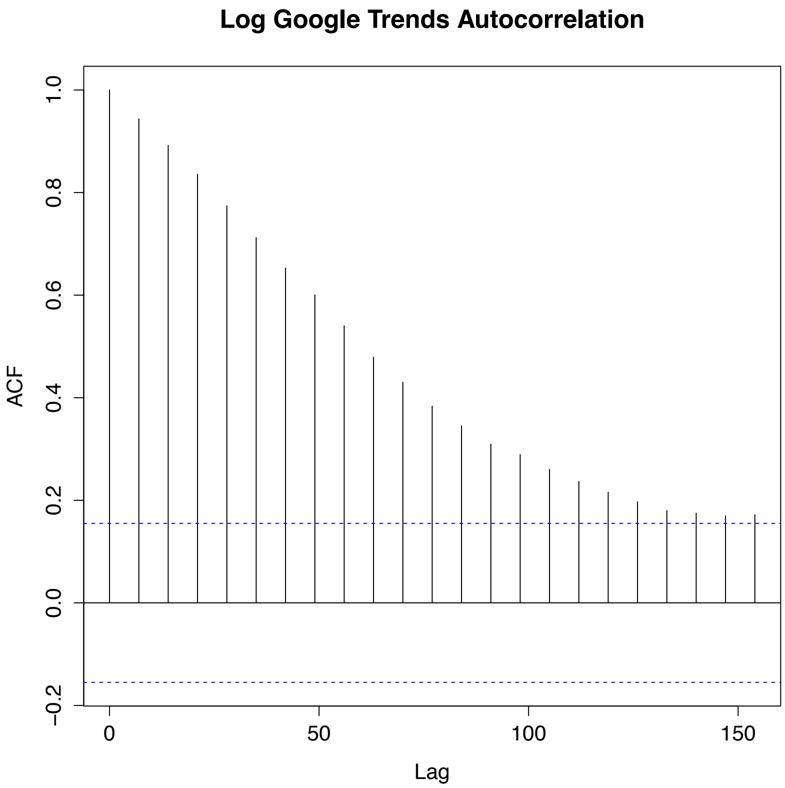
Table 10: Jarque-Bera normality test for log realized volatility

	Log realized volatility
χ^2	0.809
DOF	2
Asymptotic P-Value	0.6672

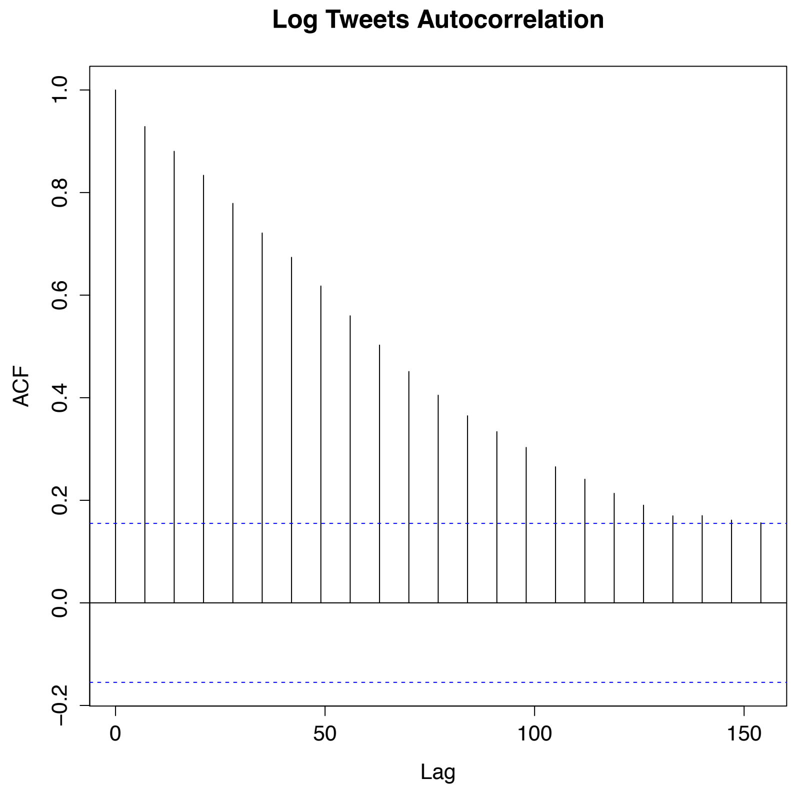
The null of normality cannot be rejected.

B Autocorrelation functions

Figures 9 & 10 show the autocorrelation functions of the log of Google Trends and tweets, and the log of realized volatility over time.



(a) Log Google Trends Autocorrelation function



(b) Log Tweets Autocorrelation function

Figure 9: Autocorrelation functions for log Google Trends and log tweets

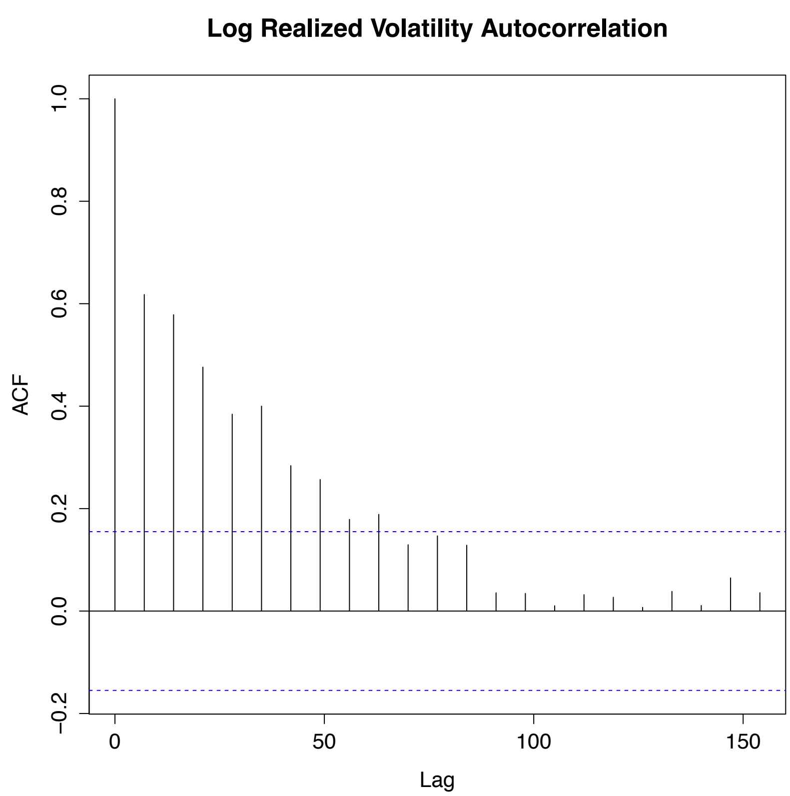


Figure 10: Log realized volatility Autocorrelation function

C Stationarity & Unit Roots

Table 11: Augmented Dickey-Fuller Test of Stationarity

	Log Realized Volatility	*Log Google Trends*	*Log Tweets*
$Dickey-Fuller$	-3.045	-2.540	-2.520
Lag order	5	5	5
P-Value	0.141	0.649	0.360

The null hypothesis of non-stationarity cannot be rejected for any of the variables, indicating the existence of a unit root. Similar tests when the data were first difference were rejected, so I conclude the series are all integrated with order 1, which allows me to use the Toda and Yamamoto approach.

I used the Kwiatowski-Phillips-Schmidt-Shin (KPSS) test to provide further evidence of the series being non-stationary (Kwiatkowski et al., 1992):

Table 12: KPSS Test for level stationarity

	Log Realized Volatility	*Log Google Trends*	*Log Tweets*
KPSS Level	0.6289	3.063	3.266
Truncation lag parameter	2	2	2
P-Value	0.02	0.000	0.000

This test has a null of stationarity; all tests are rejected in this case, meaning there is a unit root. Supplemental tests modelled in first differences failed to reject the null of stationarity, so I concluded the series were integrated with order 1.

D Weekly Returns

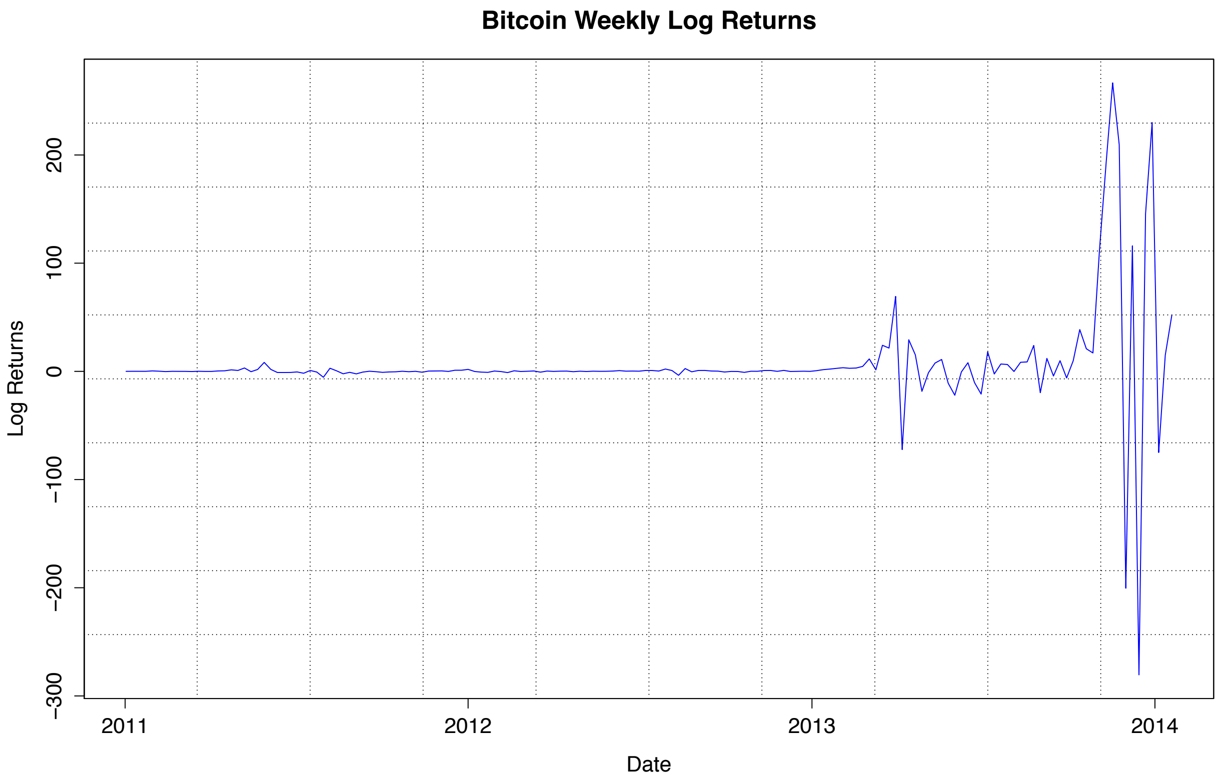


Figure 11: Bitcoin weekly log returns

January 2011 - January 2014