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TITLE: *What can explain the price, volatility and traded volume of Bitcoin?*

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What can explain the price, volatility and traded volume of Bitcoin?

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ABSTRACT

We study which variables can explain and predict the return, volatility and traded volume of the cryptocurrency Bitcoin. The explanatory variables which we investigate are return, volatility, traded volume, transaction volume, change in the number of unique Bitcoin addresses, the VIX index and Google searches for the term Bitcoin. As a volatility measure we use realized volatility calculated from high-frequency data. Studies about the price formation of Bitcoin have been conducted before, but our study is the first with an extensive analysis of the realized volatility of Bitcoin. We find that the heterogenous autoregressive model for realized volatility (Corsi, 2009), which has been recognized as a very suitable model for realized volatility of other assets, is suitable also for modeling the volatility of Bitcoin. Moreover, we find that traded volume improves volatility forecasts even further. We find that transaction volume can predict Bitcoin returns and the traded volume of Bitcoin can be predicted from Google searches.

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Preface

Cryptocurrencies have quickly become one of the most intriguing diversifiers and speculation assets on the market. Bitcoin stands out as the most popular and most volatile of all the cryptocurrencies. We have chosen to research the Bitcoin topic because it is a new interesting topic as well as it is lacking in literature. We hope our contribution will be recognized as valuable in further research on Bitcoin.

We would like to thank our thesis councilor Peter Molnar for all the help he has provided us through this writing process. We would also like to thank Steinar Veka for the help he provided when processing our data.

1. INTRODUCTION

Cryptocurrency is a relatively new phenomenon. Currency with no underlying value traded in vast online communities and networks, have become a common occurrence. It started off as a fascinating idea, and has grown to become the source of billion dollar currencies and a large speculation market. The most popular among these cryptocurrencies is Bitcoin. As of 19th of march 2017 the currency which amounts to approximately 16 million units is worth over 16 billion USD. The determinants of the price development and fundamentals of Bitcoin are not yet understood as well as for common national currencies. The interest in cryptocurrencies have exploded over the last few years, and there are already exchanges which trade futures on cryptocurrencies.

When the first Bitcoin to USD sales were made, in 2009, Bitcoin was traded at 0.07 USD per unit. This means that Bitcoin has had an increase in value of over 14 thousand times in 6 and a half years. It also has an average annualized volatility of over 5000%. This type of price development is not usual for traditional currencies, and suggests there are major differences between this new type of currency and traditional currencies. One of the unique features of Bitcoin is that all data since its conception is stored in the Bitcoin security and validation network called the Blockchain (Nakamoto, 2008), and therefore easily available for research. Also price formation of Bitcoin might be influenced by different factors than price formations of other currencies. In our article, we study the formation of return, volatility and traded volume of Bitcoin, and find indicators which can predict the variables.

Increased security development which makes Bitcoin harder to hack, will be vital for the survival of the currency. In 2014 Mt Gox, which was the largest exchange for Bitcoin at the time, released a statement saying that over a period reaching back to 2011 over 850'000 Bitcoin had been stolen from their customers. This incident plummeted the Bitcoin price and ever since hack security has been paramount for Bitcoin.

New legislation has recently been passed in Japan, making Bitcoin a legal form of payment, Keirns (2017). Bitcoin still faces some challenges being recognized in many countries across the world as legal payment, however the trend is positive regarding new legislation. These are arguments on a long list of why Bitcoin price should go up, however one large hack of an exchange or a major countrywide ban and the price plummets down again.

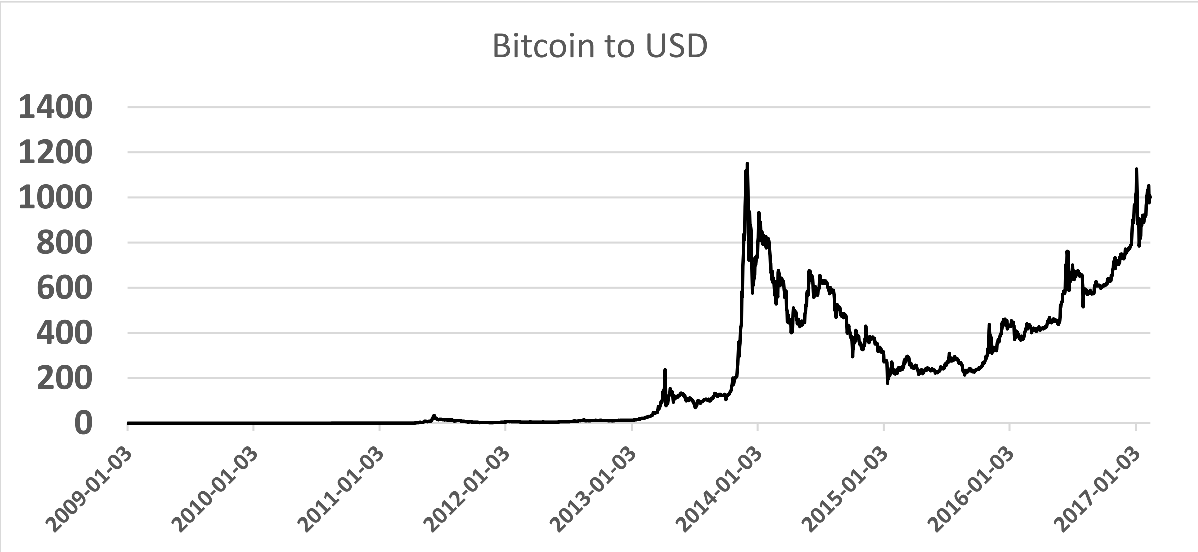

Figure 1: Market price Bitcoin since 2009 (blockchain.com)

Economic theory can be used when explaining Bitcoin in terms of being a currency, however cryptocurrency possesses uncommon traits. Bitcoin is not issued by a government, making it detached from the real economy in comparison to a traditional currency. Macroeconomic indicators do therefore not influence the Bitcoin price in the same way it influences a national currency (Kristoufek, 2013). These findings are supported in other literature by Bouoiyour and Selmi, (2015), who estimate that speculation plays a crucial role in Bitcoin price formation and Bitcoin therefore is a "speculative bubble". Kristoufek (2013) also concludes that it is difficult to determine Bitcoin prices with standard financial theory like future cash flow models. We therefore focus on various variables, including Google searches and several variables form the Bitcoin network, to investigate the relation between these variables and the return, volatility and exchange traded volume of Bitcoin.

Categorizing Bitcoin as a certain asset class is difficult and some have even rung the bell for a new asset class (Burniske et al, 2017). Trying to recreate the exposure you get from Bitcoin it was found Bitcoin has weak correlation -0.2 to 0.2 with both risky financial assets and safe-haven assets, this suggests that Bitcoin belongs to a unique and uncorrelated asset class (Bouri et al, 2017a;), (Bouri et al, 2017b;) and (Kevin, 2017). Bouri. et al (2017b;) indicate that Bitcoin can be used as a hedge against the global VIX index. However, we do not find any significant relationships between the VIX index and Bitcoins return, volatility or traded volume. Haferkorn et al. (2015) concludes that Bitcoin does not show any significant seasonality, not even the January effect observed by Wacthel (1942). We do not find any seasonality in either of the Bitcoin variables.

Since supply and demand are the main price drivers, we could expect large price swings in the future as new Bitcoin becomes scarcer, while the popularity and acceptance of the currency increases. The total amount of Bitcoin is controlled by an algorithm, which controls the amount of new Bitcoin being released into the market. This will only make the Bitcoin supply lower in the future, as the amount released is decreasing (Nakamoto, 2008).

Our research is the first which takes a deep look at how internet interest contributes to the volatility and traded volume of Bitcoin. Do general interest levels measured as Google searches contribute to the rise and fall of prices, and are interest swings an indication of price swings in Bitcoin? We also study how the volatility, return and traded volume of Bitcoin depends on common explanatory variables, like the amount traded each day and the number of people involved in trade. We attempt to not only explain, but also predict the return, the traded volume and the volatility of Bitcoin.

We are the first to investigate realized volatility of Bitcoin calculated from high frequency data. Realized volatility, introduced by Andersen and Bollerslev (1998), is a very precise measure of volatility, which makes volatility investigation much easier. It has been previously applied not only to stock markets (Christoffersen et al. 2010; Bugge at al. 2016) and major exchange rates (Andersen et al. 2001) but also to various commodities including oil (Haugom et al., 2014), gold and silver (Lyócsa and Molnár, 2016) and even electricity (Birkelund et al., 2015). However, to the best of our knowledge, nobody has studied realized volatility of Bitcoin.

Realized volatility can be conveniently modelled by a heterogeneous autoregressive model for realized volatility (Corsi, 2009). This model has been many times evaluated as a very well performing model. We therefore also use this model.

In accordance with the model of Corsi (2009), we find that past realized volatility can predict future realized volatility. Moreover, we find that also the traded volume predicts the volatility of Bitcoin. These results are in accordance with Balcilar et al (2016). We also find that Google searches for Bitcoin can predict the traded volume of Bitcoin. We find that transaction volume can predict the return of Bitcoin, and we find that Bitcoin return has a positive contemporary relationship to the number of Bitcoin addresses operational in the network. Low predictability of Bitcoin returns is in accordance with previous findings of Kristoufek (2015), Balcilar et al (2016) and Ciaian et al. (2016)

The rest of the paper is organized as follows: Section 2 introduces Bitcoin, section 3 describes the data, section 4 presents the analysis and results, and section 5 concludes.

2. INTRODUCTION TO BITCOIN

Bitcoin, launched on 9th of January 2009 is now the world's most popular cryptocurrency. It is also the world's first decentralized open source digital currency. It uses blockchain (public ledger) technology to verify transactions and avoid double spending. This peer-to-peer payment system avoids a third party and therefore represents an entirely new type of monetary transaction, eliminating the need for banks verifying the validity of a transaction. The algorithm behind Bitcoin uses the participants in the Bitcoin network to record and verify transaction as well as to create new Bitcoins.

When somebody wants to make a transaction using Bitcoin both the amount and transaction details are logged in a block, every ten minutes the block is verified and connected to the chain of previous blocks, making every transaction traceable. This makes the verification time for a Bitcoin transaction anywhere up to ten minutes depending on where in the lifecycle of the block you wish to make the transaction. Bitcoin can be said therefore not to be designed for everyday shopping, as one could in theory be standing ten minutes at the till waiting for the transaction to be accepted. However, the currency is increasingly popular for online transactions with more and more retailers accepting Bitcoin. Most Bitcoin transactions are however still tied up in exchange trade, see figure 2. Skipping a third party makes transactions cheaper and large sums of money can change hands globally much faster than usually.

The verification and connecting of the blocks is done through a phenomenon called mining. Mining utilizes computer power of the participants in the Bitcoin network. Computer power is used to solve a random digit math problem. When solved, this math problem yields a hash(code) which is the link between the new block and the chain of blocks already linked together. The miner who solved the hash is compensated in Bitcoin. To not take Bitcoin out of someone's pocket the compensation is newly generated Bitcoin and this is how new Bitcoin is created. However, in the future when most of the Bitcoin will be mined out, the reward for mining will be a small fee provided by people who wish to transfer Bitcoins. The amount of Bitcoin awarded for successful mining is controlled by an algorithm with scheduled halving's, which means that by a specific date the compensation for a hash is half of the previous period. The next halving is set to happen on 27th of June 2020. As a consequence, there exists a maximum amount of Bitcoins that will ever be released. This amount is approximately 21 million (over 16 million Bitcoins being already in circulation).

The combined computer power used to power the Bitcoin network is per 10th of February 2017 over 3,16 exaFLOPS per second, which mean it can solve $3{,}16*10^{18}$ math problems every second. The immense computer power provided by mining has therefore be drawn out as something that could power immensely complex math problems in the future. It is important to mention that these days, most of the computational power in the Bitcoin network comes from highly specialized computers that cannot be easily used for other purposes. Another downside with Bitcoin is the high electricity consumption related to the mining of Bitcoin (o'Dwyer et al, 2014).

3. DATA

The data used in this paper are collected from various sources. The sources we have used are Quandl, Blockchain, bitcoincharts.com, bitcoinity.org and Google trends. All data collected is from 1st of March 2012 to 19th of March 2017. All the data is downloaded as both daily and weekly values. We obtained the VIX index from Quandl. Blockchain is the heart of the Bitcoin trading system, and they also provide useful data on Bitcoin. We used blockchain to download data on Bitcoin returns, Bitcoin transactions and Bitcoin addresses. We downloaded the volatility data from bitcoinscharts.com. Bitcoinity.org was used to obtain traded volume of Bitcoins. Google trends was used to download search frequency on the term Bitcoin. Google trends is not case sensitive so that means it does not distinguish between "bitcoin" and "Bitcoin".

Blockchain also provides all its data seven days a week as Bitcoin has no closed days. However, to avoid possible problems with different trading patters during the working days and during the weekend, we remove the weekend data from all the datasets that included them. We use the opening price on Mondays for all our weekly variables. Next we explain how the variables are defined.

3.1 Bitcoin Return

We downloaded the Bitcoin prices from Blockchain and to make them stationary we converted prices into returns. The returns are calculated as shown in equation (1), where subscript t stands for time. Both our daily and weekly return variable are calculated in the same way.

(1) $return = Log(Price_t) - Log(Price_{t-1})$

3.2 Volatility

To have a precise measure of Bitcoins volatility we utilize the concept of realized volatility suggested by Andersen et al (1998). First we use high-frequency data to obtain 10-minute returns. Then the Realized volatility is calculated according to equation (2), where in our case Δ = 10 minutes, and $r_{t-j\Delta} = p_{t-j\Delta} - p_{t-(j+1)\Delta}$ defines continuously compounded 10-minute returns. Here, the subscript t indexes the day, while j indexes the time interval within the day t. We calculate weekly realized volatility as a simple 5-day average of daily volatilities, see equation 3. Analogically we calculate monthly volatility as a simple 22-day average of daily volatilities. We indicate the aggregation period as superscript w (weekly) or m (monthly). Since realized volatility has highly non-normal distribution, before the analysis we transform it by taking logarithm of it. For example, the weekly realized volatility used in our analysis is calculated as (4).

(2) $RV'^{d}_{t} = \sqrt{\sum_{j=0}^{M-1} r^2_{t-j-\Delta}}$

(3) $RV'^{w}_{t} = \frac{1}{5}(RV^d_t + RV^d_{t-1} + \cdots + RV^d_{t-4})$

(4) $RV^w_t = LOG(RV'^{w}_{t})$

3.3 Traded Volume

Bitcoin traded volume was obtained from bitcoinity.org. The data were obtained individually for the major exchanges and for all the smaller exchanges together as an “other” post. The Bitcoin traded volume variable was created by simply adding the traded volume from these exchanges together. Bitcoin being traded at exchanges is more common than Bitcoin being used for purchasing goods and services, see figure 2. The daily traded volume was checked for seasonality, but none was detected. The traded volume variable used in further analysis was calculated following equation (5), where subscript t stands for time and the average volume ($\overline{Volume}$) and standard deviation of average volume ($\sigma(Volume)$) are calculated over the previous year. Both daily and weekly traded volume is created this way.

$$(5)\quad Tradvol_t = \frac{Volume_t - \overline{Volume}}{\sigma(Volume)}$$

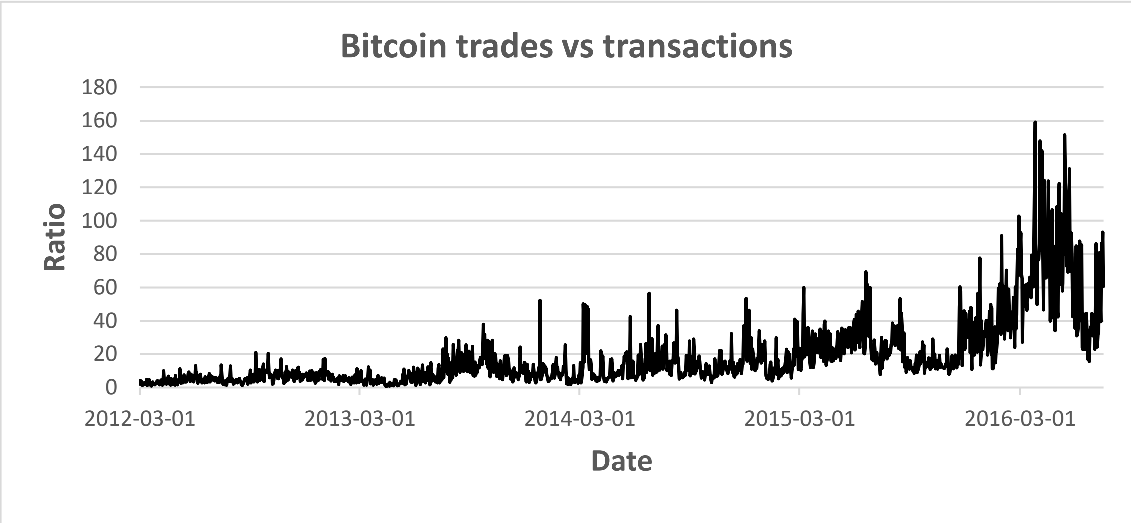

Figure 2: Bitcoin traded amount vs transaction amount (Bitcoin used for purchasing goods and services), the equation used to produce the graph is $\frac{\textbf{Traded Volume}}{\textbf{Transaction Volume}}$ *(Blockchain.com)*

3.4 Transaction Volume

Bitcoin is both traded and used for the buying of goods and services. Blockchain provides us with the number of transactions, both daily and weekly values. Transactions are defined as the number of times Bitcoin has been exchanged for goods or services, it does therefore not include the trading transactions. The daily transaction volume was checked for seasonality, but none was detected. The transaction volume variable used in further analysis was calculated following equation (6), where subscript t stands for time. The average volume ($\overline{Volume}$) and standard deviation of average volume ($\sigma(Volume)$) are calculated over the previous year. Both daily and weekly transaction volume is created this way.

$$(6)\quad Tranvol_t = \frac{Volume_t - \overline{Volume}}{\sigma(Volume)}$$

3.5 Unique addresses

The Bitcoin network is made up of different addresses which each represent a single person's account. However, one person can have several addresses. The variable was downloaded as daily data from blockchain. We transformed the original variable using equation (7), where subscript t stand for time. The daily unique addresses were checked for seasonality, but none was detected. Both the daily and weekly variable where created this way

(7) $Adresses_t = Log(Adr_t) - Log(Adr_{t-1})$

3.6 Vix Index

The data on VIX was downloaded from Quandl. The VIX index data is already stationary, but to make it more comparable to our other variables we use the change in the VIX index, defined by equation (8), where subscript t stands for time. The daily and weekly variables are both created this way.

(8) $Vix_t = Log(Vixind_t) - Log(Vixind_{t-1})$

3.7 Google trends

The data on the Google search term "Bitcoin" was obtained from Google through their Trend site. As we have mentioned Google trends are not case sensitive. Google trend data gives a normalized ratio for a search term within the time specified. The first adjustment is to make the daily and weekly data comparable over time. The daily Google trend was checked for seasonality, but none was detected. The Google trend variable used in further analysis was calculated following equation (9), where subscript t stands for time and the average volume ($\overline{Trend}$) and standard deviation of average Trend ($\sigma(Trend)$) are calculated over the previous year. Both daily and weekly Google trend is created this way. Figure 3 shows the weekly Google trend data, while figure 4 shows the transformed weekly variable.

(9) $\text{Trend}_t = \frac{Trendval_t - \overline{Trendval}}{\sigma(Trendval)}$

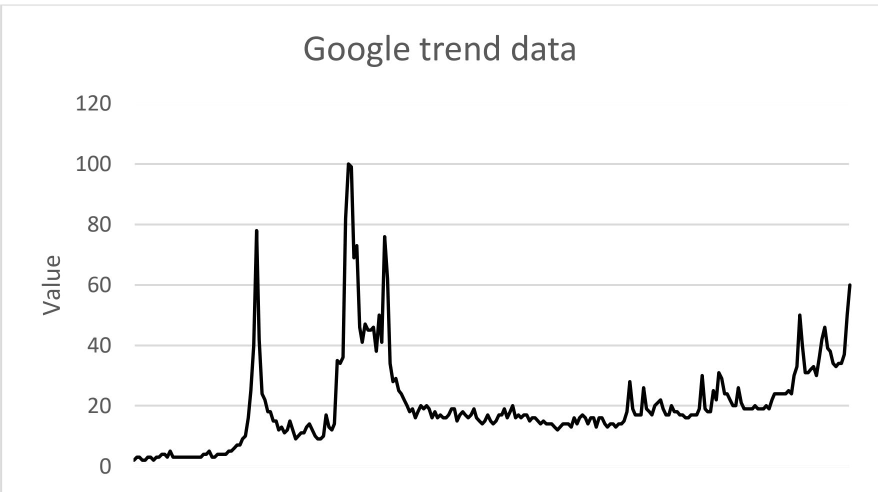

Figure 3: Weekly normalized Google trend data on the search term "Bitcoin". This is raw data obtained from Google Trends

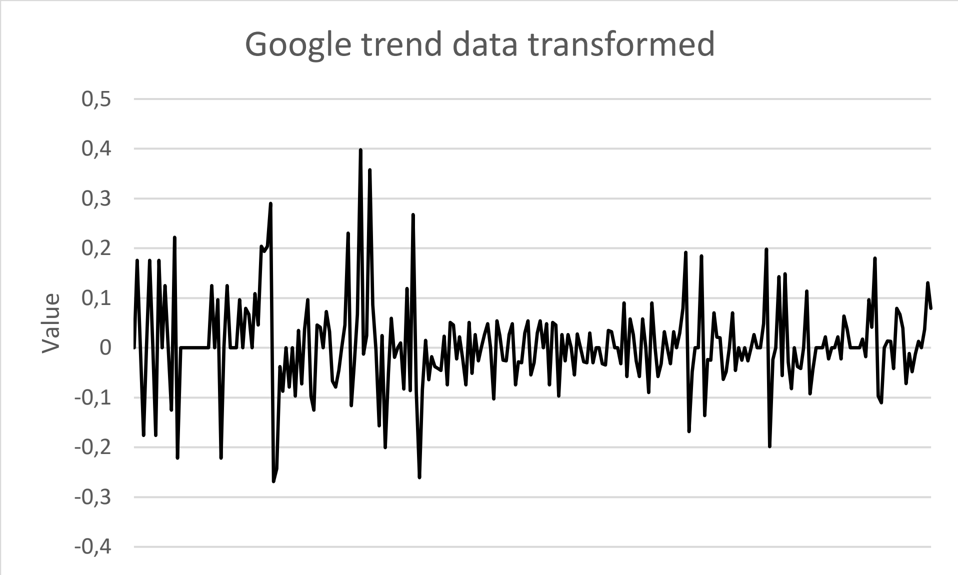

Figure 4: Weekly Google trend data, this variable has been transformed from original normalized Google trend data using equation 9: $\frac{\boldsymbol{Trendval_t} - \overline{\boldsymbol{Trendval}}}{\sigma(\boldsymbol{Trendval})}$

3.8 Statistics

Descriptive statistics and correlation matrices for our variables are presented below. The descriptive statistics for the daily data is presented in table 1. The correlation matrix for daily data is presented in table 2. The descriptive statistics for the weekly data is presented in table 3. The correlation matrix for weekly data is presented in table 4.

Table 1: Descriptive statistics for daily variables

	Mean	Median	Maximum	Minimum	Std.Dev	Skewness	Kurtosis
Realized Volatility	-1.94	-1.96	0.39	-3.45	0.54	0.64	0.73
Google Trend	0.00	0.00	0.88	-0.70	0.08	0.62	27.62
Transaction Volume	0.02	0.00	1.50	-0.60	0.16	1.35	8.55
Traded Volume	0.00	0.00	0.43	-0.38	0.49	0.37	1.28
Addresses	0.02	0.00	0.88	-0.70	0.15	0.87	1.80
VIX	0.00	0.00	0.26	-0.40	0.07	-0.64	3.14
Return	0.00	0.00	0.43	-0.38	0.05	0.67	16.94

Table 2: Correlation matrix between daily variables

	Realized Volatility	Google Trend	Transaction Volume	Traded Volume	Addresses	VIX	Return
Realized Volatility	1						
Google Trend	0.00	1					
Transaction Volume	0.02	-0.05	1				
Traded Volume	0.03	-0.17	0.20	1			
Addresses	0.01	-0.10	0.50	0.17	1		
VIX	0.03	-0.02	0.02	0.06	0.02	1	
Return	0.00	-0.05	0.01	0.00	0.01	0.04	1

Table 3: Descriptive statistics for weekly variables

	Mean	Median	Maximum	Minimum	Std.Dev	Skewness	Kurtosis
Realized Volatility	-1.87	-1.90	0.36	-2.93	0.56	0.66	0.67
Google Trend	0.02	-0.04	0.88	-0.60	0.25	0.42	1.02
Transaction Volume	0.03	0.02	1.37	-0.52	0.20	2.33	13.68
Traded Volume	0.03	0.01	1.16	-1.98	0.38	-0.67	4.38
Addresses	0.01	0.02	0.60	-0.65	0.14	-0.05	3.81
VIX	0.00	0.00	0.29	-0.24	0.07	0.54	2.50
Return	0.04	0.02	0.80	-0.43	0.15	1.57	6.20

Table 4: Correlation matrix between weekly variables.

	Realized Volatility	Google Trend	Transaction Volume	Traded Volume	Addresses	VIX	Return
Realized Volatility	1						
Google Trend	0.217	1					
Transaction Volume	0.017	0.017	1				
Traded Volume	0.177	0.012	0.130	1			
Addresses	-0.010	0.059	0.534	-0.053	1		
VIX	-0.024	0.030	0.035	0.016	0.047	1	
Return	0.116	0.163	0.224	0.103	0.395	0.002	1

4. ANALYSIS AND RESULTS

In our analysis, we use regression to find relationships between our dependent and explanatory variables. our goal is to investigate which variables can explain and predict Bitcoin returns, Bitcoin volatility and Bitcoin traded volume. Our analysis is conducted on both daily and weekly data. Equation (9) shows the model we use for our descriptive analysis, where subscript t stands for time. Equation (10) shows the model we use for our predictive analysis, where subscript t stands for time and i refers to individual explanatory variables.

(9) $Y_t = \boldsymbol{\alpha} + \sum_{i=1}^{N} B_i X_{t,i}$

(10) $Y_t = \boldsymbol{\alpha} + \sum_{i=1}^{N} B_i X_{t-1,i}$

Our models have been tested for autocorrelation and heteroskedasticity in residuals, and our statistical inference is based on robust standard errors.

4.1 BITCOIN RETURN

Daily descriptive model

In our first model, we study which variables can explain Bitcoins daily price changes. The Bitcoin daily return is our dependent variable. Our model is shown in model (1).

$$\boldsymbol{r_t = \alpha + \beta_1 GTrend_t + \beta_2 TransactionVol_t + \beta_3 TradedVol_t + \beta_4 Addresses_t + \beta_5 VIX_t + \beta_6 RV_t + \varepsilon_t} \quad \textbf{(1)}$$

The independent variables included in this model are the daily Google searches for the term "Bitcoin", transaction volume, traded volume, volatility, unique addresses used daily in the Bitcoin network and VIX. The results of model (1) are summarized in Table 5.

Table 5 Regression results of model 1, tested with different variable inclusion (values in parentheses are standard errors. One star indicates significance at the 5% level and two stars indicates significance at the 1% level) $\boldsymbol{R^2}$ *are for each model is included on the final line of each model.*

	Dr.1	Dr.2	Dr.3	Dr.4	Dr.5	Dr.6	Dr.7
Intercept	0.00**	0.01**	0.01**	0.00**	0,00**	0.00	0,00
	(0.001)	*(0.001)*	*(0.001)*	*(0.001)*	*(0.001)*	*(0.015)*	*(0.015)*
Google Trend$_t$	0.00						-0.03
	(0.023)						*(0.022)*
Transaction Volume$_t$		0.01					-0.01
		(0,007)					*(0.009)*
Traded Volume$_t$			0.00				-0.01
			(0.003)				*(0.003)*
Addresses$_t$				0.03**			0.04**
				(0.011)			*(0.013)*
VIX$_t$					-0.01		0.00
					(0.016)		*(0.017)*
Realized Volatility$_t$						0.00	0.00
						(0.005)	*(0.005)*
Model R^2	0.00	0.00	0.00	0.01	0.00	0.00	0.01

Transaction volume, traded volume, Google trends, realized volatility and the VIX index are all insignificant when tested, both in the univariate regression and in the multivariate regression. The only explanatory variable that is significant are the unique addresses used in the Bitcoin network. The addresses variable is significant for Dr.4 and Dr.7, this indicates a relationship between the number of users in the Bitcoin network every day and the price changes of Bitcoin. However, the R^2 value of the multivariate model is 0,01, which means our model can explain only 1% of the variation in Bitcoins return.

Daily predictive model

In our second model, we study which variables can predict Bitcoins daily price changes. The Bitcoin daily return is our dependent variable. We estimate the following regression, see model (2)

$$\boldsymbol{r_t = \alpha + \beta_1 GTrend_{t-1} + \beta_2 TransactionVol_{t-1} + \beta_3 TradedVol_{t-1} + \beta_4 Addresses_{t-1} + \beta_5 VIX_{t-1} + \beta_6 RV_{t-1} + \varepsilon_t} \qquad \textbf{(2)}$$

The variables included are all daily data. The results of model (2) are summarized in Table 6.

Table 6 Regression results of model 2, tested with different variable inclusion (values in parentheses are standard errors. One star indicates significance at the 5% level and two stars indicates significance at the 1% level) $\boldsymbol{R^2}$ *are for each model is included on the final line of each model.*

	Drp.1	Drp.2	Drp.3	Drp.4	Drp.5	Drp.6	Drp.7
Intercept	0.00**	0.01**	0.00**	0.00**	0.00**	0.02	0.02
	(0.001)	*(0.001)*	*(0.001)*	*(0.001)*	*(0.001)*	*(0.013)*	*(0.013)*
Google Trend$_{t-1}$	0.00						0.01
	(0.025)						*(0.024)*
Transaction Volume$_{t-1}$		0.03**					0.02*
		(0.008)					*(0.008)*
Traded Volume$_{t-1}$			0.00				0.00
			(0.004)				*(0.004)*
Addresses$_{t-1}$				0.03**			0.02
				(0.012)			*(0.012)*
VIX$_{t-1}$					-0.01		0.00
					(0.018)		*(0.017)*
Realized Volatility$_{t-1}$						0.00	0.01
						(0.001)	*(0.001)*
Model R^2	0.00	0.01	0.00	0.01	0.00	0.00	0.01

Traded volume, Google trends, realized volatility and the VIX index are all insignificant when tested, both in the univariate regression and in the multivariate regression. The unique address variable is significant when tested in Drp.4 however when tested in Drp.7 it is deemed non-significant, this might be due to its correlation with transaction volume as seen in table 6 (Gordon, 1968). The transaction volume is significant for both Drp.2 and Drp.7. This indicates a relationship between transaction volume of Bitcoin and future returns. However, we have a R^2 value of 0,01, which means that our model can explain only 1% of the variation in Bitcoin returns.

Weekly descriptive model

In our third regression model, we study which variables can explain Bitcoins weekly price changes. We use the return of Bitcoin as our dependent variable. Our model is shown in model (3).

$$\boldsymbol{r_t = \alpha + \beta_1 GTrend_t + \beta_2 TransactionVol_t + \beta_3 TradedVol_t + \beta_4 Addresses_t + \beta_5 VIX_t + \beta_6 RV_t + \varepsilon_t} \qquad \textbf{(3)}$$

The explanatory variables in this regression model are all weekly variables. The results of model (3) are summarized in table 7.

Table 7 Regression results of model 3, tested with different variable inclusion (values in parentheses are standard errors. One star indicates significance at the 5% level and two stars indicates significance at the 1% level) $\boldsymbol{R^2}$ *are for each model is included on the final line of each model.*

	Wr.1	Wr.2	Wr.3	Wr.4	Wr.5	Wr.6	Wr.7
Intercept	0.03**	0.03**	0.03**	0.02**	0.03**	0.16	0.13
	(0.008)	*(0.008)*	*(0.008)*	*(0.008)*	*(0.008)*	*(0.097)*	*(0.080)*
Google Trend$_t$	0.10						0.08
	(0.076)						*(0.066)*
Transaction Volume$_t$		0.13**					0.01
		(0.050)					*(0.036)*
Traded Volume$_t$			0.03				0.02
			(0.029)				*(0.027)*
Addresses$_t$				0.31**			0.31**
				(0.077)			*(0.077)*
VIX$_t$					0.01		0.00
					(0.103)		*(0.102)*
Realized Volatility$_t$						0.01	0.01
						(0.005)	*(0.004)*
Model R^2	0.02	0.03	0.00	0.11	0.00	0.02	0.13

The variables traded volume, realized volatility, VIX and the Google trend variables all give insignificant results. Transaction volume is significant in model Wr.2, but not in the multivariate model Wr.7. These results are likely due to its correlation with the unique addresses variable as seen in table4 (Gordon,1968).
The unique addresses variable is significant in both Wr.4 and Wr.7. The addresses variable is significant in our descriptive model on both the daily and weekly level. The R^2 value is 0.13 for Wr.7, which is significantly higher than our daily models and the highest R^2 of our return analysis. This means our model can explain 13% of the variation in the return of Bitcoin.

Weekly predictive model

In our fourth regression model, we study which variables can predict Bitcoins weekly price changes. We estimate the following regression model, which is shown in model (4).

$$\boldsymbol{r_t = \alpha + \beta_1 GTrend_{t-1} + \beta_2 TransactionVol_{t-1} + \beta_3 TradedVol_{t-1} + \beta_4 Addresses_{t-1} + \beta_5 VIX_{t-1} + \beta_6 RV_{t-1} + \varepsilon_t} \qquad \textbf{(4)}$$

The explanatory variables in this regression model are all weekly variables. The results of model (4) are summarized in table 8.

Table 8 Regression results of model 4, tested with different variable inclusion (values in parentheses are standard errors. One star indicates significance at the 5% level and two stars indicates significance at the 1% level) $\boldsymbol{R^2}$*are for each model is included on the final line of each model.*

	Wrp.1	Wrp.2	Wrp.3	Wrp.4	Wrp.5	Wrp.6	Wrp.7
Intercept	0.00**	0.01**	0.01**	0.00**	0.00**	0.00	0.12
	(0.008)	*(0.008)*	*(0.008)*	*(0.008)*	*(0.008)*	*(0.094)*	*(0.086)*
Google Trend$_{t-1}$	0.00						0.08
	(0.062)						*(0.058)*
Transaction Volume$_{t-1}$		0.01					0.05
		(0.025)					*(0.054)*
TradedVolume$_{t-1}$			0.00				0.01
			(0.030)				*(0.027)*
Addresses$_{t-1}$				0.03*			0.15
				(0.093)			*(0.082)*
VIX$_{t-1}$					-0.01		-0.10
					(0.095)		*(0.093)*
Realized Volatility$_{t-1}$						0.00	0.05
						(0.004)	*(0.004)*
Model R^2	0.00	0.00	0.00	0.01	0.00	0.00	0.06

The Google trends, realized volatility, Transaction volume, VIX and traded volume variables are insignificant. Unique addresses is the only variable with significant results. In Wrp.4 the unique addresses variable is significant under 5%, however in the Wrp.7 it is no longer significant. Comparing the unique addresses of the daily and weekly predictive regression we find that the significance of unique addresses improves as the time horizon of the regression increases. Transaction volume which was significant at the daily level is no longer significant at the weekly level. The R^2 of the multivariate model is 0.06, which means the model can explain 6% of the variation in the return of Bitcoin.

4.2 BITCOIN REALIZED VOLATILITY

The realized volatility variables we use in our realized volatility model are proposed by Corsi (2009). His model proposes an additive volatility cascade inspired by the heterogenous market hypothesis, which has the feature of considering realized volatility over different time intervals. The HAR-RV model successfully captures the long-memory behavior of volatility, and it also exhibits remarkable forecasting abilities. The HAR-RV model has proven time and time again to outperform short-memory models at all time horizons considered and performs at par with the far more complicated ARFIMA model (Cheung, 1993). Corsi (2009) suggests using the logic of his results in different volatility models.

The simplicity of this model translates well to the research we propose to do. We therefore implement the suggested format of including previous Bitcoin realized volatility variables at three different time horizons, to forecast Bitcoins realized volatility. We include past daily, weekly and monthly volatility as explanatory variables in our daily analysis. In our analysis of weekly data, we include past weekly and monthly realized volatility.

As our results show the heterogenous autoregressive approach proves beneficial for our research and much of the variation in Bitcoins realized volatility can be explained through the HAR-RV approach and its lagged volatility variables.

Daily descriptive model

The fifth regression model is the first model where we look at the realized volatility of Bitcoin. We study which variables can explain Bitcoins daily realized volatility changes. Our model is shown in model (5).

$$\boldsymbol{RV_t = \alpha + \beta_1 VolD_{t-1} + \beta_2 VolW_{t-1} + \beta_3 VolM_{t-1} + \beta_4 GTrend_t + \beta_5 TransactionVolume_t + \beta_6 TradVolume_t + \beta_7 Addresses_t + \beta_8 VIX_t + \beta_9 r_t + \varepsilon_t} \qquad \textbf{(5)}$$

The dependent variable used is the realized volatility of Bitcoin. The explanatory variables used is the lagged daily volatility of Bitcoin, lagged weekly volatility of Bitcoin, lagged monthly volatility of Bitcoin, transaction volume, traded volume, unique addresses used, the VIX index, returns and Google searches for the term "Bitcoin". The results of model (5) are shown in table 9.

Table 9 Regression results of model 5, tested with different variable inclusion (values in parentheses are standard errors. One star indicates significance at the 5% level and two stars indicates significance at the 1% level) $\boldsymbol{R^2}$ *are for each model is included on the final line of each model.*

	Drv.1	Drv.2	Drv.3	Drv.4	Drv.5	Drv.6	Drv.7	Drv.8
Intercept	-0.25**	-0.24**	-0.18**	-0.26**	-0.24**	-0.25**	-2.86**	-0.21**
	(0.064)	*(0.063)*	*(0.064)*	*(0.054)*	*(0.063)*	*(0.064)*	*(0.063)*	*(0.052)*
Volatiltity Daily$_{t-1}$	0.31**	0.30**	0.35**	0.55**	0.33**	0.32**	0.38**	0.56**
	(0.035)	*(0.035)*	*(0.035)*	*(0.031)*	*(0.034)*	*(0.034)*	*(0.034)*	*(0.030)*
Volatility Weekly$_{t-1}$	0.40**	0.40**	0.40**	0.25**	0.40**	0.41**	0.40**	0.24**
	(0.043)	*(0.043)*	*(0.042)*	*(0.036)*	*(0.042)*	*(0.043)*	*(0.042)*	*(0.035)*
Volatility Monthly$_{t-1}$	0.21**	0.21**	0.20**	0.14**	0.20**	0.21**	0.20**	0.14**
	(0.035)	*(0.036)*	*(0.034)*	*(0.031)*	*(0.034)*	*(0.035)*	*(0.035)*	*(0.030)*
Google Trend$_t$		0.27*						0.22*
		(0.128)						*(0.102)*
Transaction Volume$_t$			0.22**					0.06
			(0.077)					*(0.070)*
Traded Volume$_t$				0.39**				0.39**
				(0.024)				*(0.023)*
Addresses$_t$					0.27**			0.12**
					(0.077)			*(0.074)*
VIX$_t$						0.05		0.17
						(0.126)		*(0.104)*
Return$_t$							1.72**	0.36
							(0.402)	(0.209)
Model R^2	0.71	0.71	0.71	0.78	0.71	0.71	0.71	0.78

Using daily, weekly and monthly realized volatility as a prediction variable of the daily realized volatility yields a high R^2 value and the variables are significant at the 1% for all model specifications. The VIX variable is not significant. The return variable is significant in Drv7, but not In Drv.8. The traded volume variable is significant under 1% for in both Drv.4 and Drv.8. Google Trends is also deemed significant under 5% by Drv.8 and Drv.2. The addresses variable is significant in Drv.5 and Drv.8. Google trends, addresses and traded volumes indicate a significant relationship to the realized volatility formation of Bitcoin. The transaction volume is significant in Drv.3, but we can see from table 2 that it has strong correlation to traded volume which explains why it is no longer significant in Drv.8 (Gordon, 1968). The R^2 of Drv.8 is 0.78, which means that the model can explain 78% of the variation in the realized volatility of Bitcoin. However, the model containing only past volatilities has the R^2 of 0.71. Moreover, the R^2 of model Drv.3, which contains only past volatilities and traded volume, is also 0.78. This means that except for the past volatilities, the variable which can explain the volatility the most is clearly the traded volume.

Daily predictive regression

In our fifth regression, we study which variables can predict Bitcoins daily realized volatility changes. Our model is shown in model (6).

$$\boldsymbol{RV_t = \alpha + \beta_1 VolD_{t-1} + \beta_2 VolW_{t-1} + \beta_3 VolM_{t-1} + \beta_4 GTrend_{t-1} + \beta_5 TransactionVol_{t-1} + \beta_6 TradedVol_{t-1} + \beta_7 Addresses_{t-1} + \beta_8 VIX_{t-1} + \beta_9 r_{t-1} + \varepsilon_t} \quad \textbf{(6)}$$

These variables are daily values. The results of model (6) are shown in table 10.

Table 10 Regression results of model 6, tested with different variable inclusion (values in parentheses are standard errors. One star indicates significance at the 5% level and two stars indicates significance at the 1% level) $\boldsymbol{R^2}$*are for each model is included on the final line of each model.*

	Drvp.1	Drvp.2	Drvp.3	Drvp.4	Drvp.5	Drvp.6	Drvp.7	Drvp.8
Intercept	-0.24**	-0.25**	-0.24**	-0.27**	-0.24**	-0.24**	-2.86**	0.30**
	(0.064)	*(0.063)*	*(0.065)*	*(0.064)*	*(0.064)*	*(0.064)*	*(0.064)*	*(0.061)*
Volatility Daily$_{t-1}$	0.31**	0.31**	0.31**	0.29**	0.32**	0.32**	0.31**	0.28**
	(0.034)	*(0.034)*	*(0.035)*	*(0.036)*	*(0.035)*	*(0.034)*	*(0.036)*	*(0.035)*
Volatility Weekly$_{t-1}$	0.40**	0.41**	0.41**	0.42**	0.41**	0.40**	0.41**	0.41**
	(0.042)	*(0.043)*	*(0.043)*	*(0.043)*	*(0.043)*	*(0.043)*	*(0.042)*	*(0.042)*
Volatility Monthly$_{t-1}$	0.21**	0.21**	0.21**	0.21**	0.21**	0.20**	0.20**	0.22**
	(0.035)	*(0.036)*	*(0.035)*	*(0.035)*	*(0.035)*	*(0.035)*	*(0.035)*	*(0.035)*
Google Trend$_{t-1}$		0.27*						0.27*
		(0.128)						(0.126)
Transaction Volume$_{t-1}$			0.03					0.00
			(0.073)					(0.075)
Traded Volume$_{t-1}$				0.06**				0.06**
				(0.019)				(0.019)
Addresses$_{t-1}$					0.03			0.01
					(0.066)			(0.064)
VIX$_{t-1}$						0.04		-0.04
						(0.126)		*(0.127)*
Return$_{t-1}$							1.86**	0.51*
							(0.407)	(0.252)
Model R^2	0.71	0.71	0.71	0.71	0.71	0.71	0.71	0.71

Log Daily, Log Monthly and Log Weekly are significant under 1% in all our models. These variables are the same as in model 5 and we therefore expect close to identical results.

Transaction volume, unique addresses and the VIX variables are insignificant. Only traded volume, returns and Google trends give significant results. Traded volume is significant under 1% in both Drvp.4 and Drvp.8. Google trends is significant at the 5% level in Drvp.2 and Drvp.8. Return is significant in both Drvp.7 and Drvp.8. Traded volume, Google trends and traded volume all indicate a predictive relationship to the realized volatility of Bitcoin. The R^2 of Drvp.8 is 0.71, which means that the model can explain 71% of the variation in the realized volatility of Bitcoin. We see that most of the variation is still explained by the volatility variables.

Weekly descriptive regression

In our seventh regression model, we study which variables can describe Bitcoins weekly realized volatility changes. Our model is shown in model (7).

$$\boldsymbol{RV_t = \alpha + \beta_1 VolW_{t-1} + \beta_2 VolM_{t-1} + \beta_3 GTrend_t + \beta_4 TransactionVol_t + \beta_5 TradedVol_t + \beta_6 Addresses_t + \beta_7 VIX_t + \beta_8 r_t + \varepsilon_t} \qquad \textbf{(7)}$$

The variables are all weekly values. The results of model (7) are shown in table 11.

Table 11 Regression results of model 7, tested with different variable inclusion (values in parentheses are standard errors. One star indicates significance at the 5% level and two stars indicates significance at the 1% level) $\boldsymbol{R^2}$ *are for each model is included on the final line of each model.*

	Wrv.1	Wrv.2	Wrv.3	Wrv.4	Wrv.5	Wrv.6	Wrv.7	Wrv.8
Intercept	0.47**	0.44**	0.48**	0.48**	0.48**	0.48**	-1.96**	0.49**
	(0.141)	*(0.133)*	*(0.141)*	*(0.142)*	*(0.141)*	*(0.141)*	*(0.0142)*	*(0.128)*
Volatility Weekly$_{t-1}$	0.16**	0.15**	0.15**	0.15**	0.16**	0.16**	0.16**	0.15**
	(0.052)	*(0.053)*	*(0.051)*	*(0.025)*	*(0.053)*	*(0.052)*	*(0.53)*	*(0.053)*
Volatility Monthly$_{t-1}$	0.73**	0.73**	0.74**	0.73**	0.73**	0.73**	0.74**	0.74**
	(0.069)	*(0.069)*	*(0.069)*	*(0.070)*	*(0.069)*	*(0.070)*	*(0.069)*	*(0.067)*
Google Trend$_t$		0.20						0.24
		(0.132)						*(0.130)*
Transaction Volume$_t$			0.12					0.28*
			(0.96)					*(0.124)*
Traded Volume$_t$				0.01				0.02
				(0.052)				*(0.053)*
Addresses$_t$					-0.13			-0.31
					(0.149)			*(0.195)*
VIX$_t$						-0.02		-0.04
						(0.296)		*(0.281)*
Return$_t$							0.80	-0.24
							(0.420)	*(0.208)*
Model R^2	0.69	0.70	0.69	0.69	0.69	0.69	0.70	0.70

The volatility variables are all significant. Google trends, returns, traded volume, unique addresses and the VIX variables are insignificant when tested against the weekly realized volatility. The only significant result found for any of the non-volatility variables is the transaction volume in the full model Wrv.7. The R^2 value of Wrv.8 is 0.7, which means that we can explain 70% of the variance in the realized volatility of Bitcoin through our model. As seen from the model most of the variation is explained from the volatility variables.

Weekly predictive regression

In our eight regression model, we study which variables can predict Bitcoins weekly realized volatility changes. Our model is shown in model (8).

$$\boldsymbol{RV_t = \alpha + \beta_1 VolW_{t-1} + \beta_2 VolM_{t-1} + \beta_3 GTrend_{t-1} + \beta_4 TransactionVol_{t-1} + \beta_5 TradedVol_{t-1} + \beta_6 Adresses_{t-1} + \beta_7 VIX_{t-1} + \beta_8 r_{t-1} + \varepsilon_t} \quad \textbf{(8)}$$

The variables are all weekly values. The results of model (8) are shown in table 12.

Table 12 Regression results of model 8, tested with different variable inclusion (values in parentheses are standard errors. One star indicates significance at the 5% level and two stars indicates significance at the 1% level) $\boldsymbol{R^2}$ *are for each model is included on the final line of each model.*

	Wrvp.1	Wrvp.2	Wrvp.3	Wrvp.4	Wrvp.5	Wrvp.6	Wrvp.7	Wrvp.8
Intercept	0.50**	0.49**	0.50**	0.47**	0.49**	0.50**	-1.96**	0.47**
	(0.141)	*(0.142)*	*(0.143)*	*(0.142)*	*(0.140)*	*(0.144)*	*(0.143)*	*(0.130)*
Volatility Weekly$_{t-1}$	0.13**	0.14**	0.13**	0.14**	0.13**	0.14**	0.14**	0.15*
	(0.052)	*(0.054)*	*(0.054)*	*(0.054)*	*(0.055)*	*(0.054)*	*(0.054)*	*(0.063)*
Volatility Monthly$_{t-1}$	0.76**	0.76**	0.77**	0.75**	0.76**	0.76**	0.75**	0.75**
	(0.069)	*(0.070)*	*(0.073)*	*(0.073)*	*(0.074)*	*(0.073)*	*(0.073)*	*(0.073)*
Google Trend$_{(t-1)}$		0.06						0.09
		(0.096)						*(0.094)*
Transaction Volume$_{t-1}$			-0.05					-0.12
			(0.090)					*(0.108)*
Traded Volume$_{t-1}$				0.11				0.11
				(0.063)				*(0.063)*
Addresses$_{t-1}$					0.12			0.22
					(0.152)			*(0.185)*
VIX$_{t-1}$						-0.29		-0.34
						(0.302)		*(0.290)*
Return$_{t-1}$							0.80	-0.20
							(0.420)	*(0.203)*
Model R^2	0.69	0.69	0.69	0.70	0.69	0.69	0.70	0.70

The volatility variables representing the previous weekly and monthly volatility values are significant. The Google trends, returns, transaction volume, traded volume, unique addresses and the VIX variables are insignificant in all our models, proving that our model struggles to predict Bitcoin volatility on a weekly scale. The R^2 of Wrvp.8 is 0.7, which means our model can explain 70% of the variation in realized volatility of Bitcoin. We still see that most of the variation is explained by the volatility variables.

Our analysis shows that volatility is best predicted at the daily level.

4.3 BITCOIN TRADED VOLUME

Daily descriptive regression

In our ninth regression model, we study which variables can describe Bitcoins daily traded volume. Our model is shown in model (9).

$$\boldsymbol{Tradedvolume_t = \alpha + \beta_1 GTrend_t + \beta_2 TransactionVol_t + \beta_3 Addresses_t + \beta_4 VIX_t + \beta_5 r_t + \beta_6 RV_t + \varepsilon_t} \qquad \textbf{(9)}$$

We use traded volume as our dependent variable. Our explanatory variables are Google searches on the term Bitcoin, the return on Bitcoin, the VIX, volatility, unique addresses and the transaction volume of Bitcoin. The variables included are all daily values. The results of model (9) are shown in table 13.

Table 13 Regression results of model 9, tested with different variable inclusion (values in parentheses are standard errors. One star indicates significance at the 5% level and two stars indicates significance at the 1% level) $\boldsymbol{R^2}$ *are for each model is included on the final line of each model.*

	Dtv.1	Dtv.2	Dtv.3	Dtv.4	Dtv.5	Dtv.6	Dtv.7
Intercept	-0.02	-0.03*	-0.02	-0.03*	-0.02	-0.62**	-0.57**
	(0.013)	*(0.013)*	*(0.013)*	*(0.013)*	*(0.013)*	*(0.072)*	*(0.069)*
Google trend$_t$	-1.13**						-1.01**
	(0.241)						*(0.215)*
Addresses$_t$		0.69**					0.42**
		(0.155)					*(0.128)*
VIX$_t$			0.12				0.13
			(0.170)				*(0.167)*
Transaction Volume$_t$				0.54**			0.24
				(0.114)			*(0.126)*
Return$_t$					-0.27		-0.46
					(0.334)		*(0.303)*
Realized Volatility$_t$						-0.21**	-0.19**
						(0.024)	*(0.023)*
Model R^2	0.04	0.04	0.00	0.03	0.00	0.07	0.12

VIX and returns are insignificant. The transaction volume variable is significant in Dtv.4, but not in Dtv.7. The Unique addresses variable is significant in Dtv.2 and Dtv.7. Google trends are significant in Dtv.1 and Dtv.7. The realized volatility is significant in Dtv.6 and Dtv.7. This indicates an explanatory relationship between the unique addresses, Google trends, realized volatility and the traded volume of Bitcoin. The R^2 value of our multivariate model is 0.12, which means that our model can explain 12% of the variation in the traded volume of Bitcoin.

Daily predictive model

In our tenth model, we study which variables can predict Bitcoins daily traded volume. Our model is shown in model (10).

$$\boldsymbol{Tradedvolume_t = \alpha + \beta_1 GTrend_{t-1} + \beta_2 TransactionVol_{t-1} + \beta_3 Addresses_{t-1} + \beta_4 VIX_{t-1} + \beta_5 r_{t-1} + \beta_6 RV_{t-1} + \varepsilon_t} \quad \textbf{(10)}$$

All variables included are daily values. The results for model (10) are shown in table 14.

Table 14 Regression results of model 10, tested with different variable inclusion (values in parentheses are standard errors. One star indicates significance at the 5% level and two stars indicates significance at the 1% level) $\boldsymbol{R^2}$ *are for each model is included on the final line of each model.*

	Dtvp.1	Dtvp.2	Dtvp.3	Dtvp.4	Dtvp.5	Dtvp.6	Dtvp.7
Intercept	-0.20	-0.02	-0.02	-0.02	-0.02	-0.03	0.28*
	(0.013)	*(0.013)*	*(0.013)*	*(0.013)*	*(0.013)*	*(0.086)*	*(0.084)*
Google trend$_{t-1}$	0.25						-0.03
	(0.271)						*(0.232)*
Addresses$_{t-1}$		-0.12					0.02
		(0.094)					*(0.155)*
VIX$_{t-1}$			0.12				0.38
			(0.171)				*(0.171)*
Transaction Volume$_{t-1}$				-0.08			-0.19
				(0.090)			*(0.122)*
Return$_{t-1}$					0.41		0.07
					(0.318)		*(0.374)*
Realized Volatility$_{t-1}$						0.00	0.01
						(0.004)	*(0.004)*
Model R^2	0.00	0.00	0.00	0.00	0.00	0.00	0.01

We have no significant results and can therefore not indicate any predictive relationships between our explanatory variables and the traded volume of Bitcoin on a daily scale. The R^2 value of our model is 0.01, which means our model can explain only 1% of the variation in the traded volume of Bitcoin.

Weekly descriptive regression

In our eleventh model, we study which variables can describe Bitcoins weekly traded volume. Our model is shown in model (11)

$$\boldsymbol{Tradedvolume_t = \alpha + \beta_1 GTrend_t + \beta_2 TransactionVol_t + \beta_3 Addresses_t + \beta_4 VIX_t + \beta_5 r_t + \beta_6 RV_t + \varepsilon_t} \qquad \textbf{(11)}$$

All variables included are weekly values. The results for model (11) are shown in table 15.

Table 15 Regression results of model 11, tested with different variable inclusion (values in parentheses are standard errors. One star indicates significance at the 5% level and two stars indicates significance at the 1% level) $\boldsymbol{R^2}$*are for each model is included on the final line of each model.*

	Wtv.1	Wtv.2	Wtv.3	Wtv.4	Wtv.5	Wtv.6	Wtv.7
Intercept	0.02	0.02	0.02	0.02	0.01	0.44**	0.43**
	(0.021)	*(0.022)*	*(0.021)*	*(0.022)*	*(0.021)*	*(0.138)*	*(0.134)*
Google $trend_t$	0.01						-0.04
	(0.107)						*(0.107)*
$Addresses_t$		-0.10					0.04
		(0.162)					*(0.209)*
VIX_t			0.20				0.24
			(0.269)				*(0.274)*
Transaction $Volume_t$				-0.19			-0.23
				(0.106)			*(0.133)*
$Return_t$					0.17		0.14
					(0.202)		*(0.202)*
Realized $Volatility_t$						0.02**	0.02**
						(0.007)	*(0.006)*
Model R^2	0.00	0.00	0.00	0.01	0.00	0.03	0.03

The variables Google trend, VIX, transaction volume, traded volume, return and addresses are not significant. The realized volatility variable is significant in Wtv.6 and Wtv.7. This indicates an explanatory relationship between the realized volatility of Bitcoin and the traded volume of Bitcoin. The R^2 value of our multivariate model is 0.03, which means our model can explain 3% of the variation in the traded volume of Bitcoin. However, the model that includes just the realized volatility performs equally well.

Weekly Predictive model

In our twelfth regression model, we study which variables can predict Bitcoins weekly traded volume. Our model is shown in model (12).

$$\boldsymbol{Tradedvolume_t = \alpha + \beta_1 GTrend_{t-1} + \beta_2 TransactionVol_{t-1} + \beta_3 Addresses_{t-1} + \beta_4 VIX_{t-1} + \beta_5 r_{t-1} + \beta_6 RV_{t-1} + \varepsilon_t} \qquad \textbf{(12)}$$

All the variables included are weekly. The results for model (12) are shown in table 16.

Table 16 Regression results of model 12, tested with different variable inclusion (values in parentheses are standard errors. One star indicates significance at the 5% level and two stars indicates significance at the 1% level) $\boldsymbol{R^2}$*are for each model is included on the final line of each model.*

	Wtvp.1	Wtvp.2	Wtvp.3	Wtvp.4	Wtvp.5	Wtvp.6	Wtvp.7
Intercept	0.01	0.01	0.01	0.01	0.00	0.28*	-0.09
	(0.020)	*(0.021)*	*(0.021)*	*(0.021)*	*(0.022)*	*(0.139)*	*(0.135)*
Google trend$_{t-1}$	0.57**						-1.00**
	(0.141)						*(0.109)*
Addresses$_{t-1}$		0.12					0.20
		(0.169)					*(0.193)*
VIX$_{t-1}$			-0.09				0.02
			(0.259)				*(0.264)*
Transaction Volume$_{t-1}$				0.20			0.41**
				(0.113)			*(0.131)*
Return$_{t-1}$					0.43*		0.29
					(0.204)		*(0.205)*
Realized Volatility$_{t-1}$						0.01*	-0.01
						(0.007)	*(0.006)*
Model R^2	0.05	0.00	0.00	0.01	0.02	0.01	0.11

The variables VIX, transaction volume and addresses are not significant. The volatility variable is significant in Wtvp.6, but not in Wtvp.7. Our transaction volume variable is not significant in Wtvp.4 but is in Wtvp.7. Returns has significant results in Wtvp.6, but not in Wtvp.7. The Google trends are significant in both Wtvp.1 and Wtvp.7. Our analysis indicates that there is predictive relationship between Google searches for the term Bitcoin and the traded volume of Bitcoin. The R^2 value of our full model is 0.11, which means our model can explain 11% of the variation in the traded volume of Bitcoin.

Our analysis shows that the traded volume is better predicted at a weekly level, however the descriptive analysis had better results at the daily level.

5. CONCLUSION

In this paper, we study which variables are useful in explaining and predicting returns, volatility and traded volume of Bitcoin. We find that the individual changes in unique addresses can explain Bitcoins return formation at both a weekly and daily time horizon. Transaction volume of Bitcoin was found to have a relationship to return formation in our predictive daily model, but not in our weekly predictive model. Traded volume was not found to have any significant relationship to Bitcoins return. Even though our results indicate some relationships with the explanatory variables, the variation of the return is still left mostly unexplained by our regression models. In other words, Bitcoin returns are mostly unpredictable. This feature of Bitcoin is similar to the properties of other financial assets, where prediction of price changes is extremely difficult.

In our study of Bitcoin volatility, we utilize realized volatility calculated from high-frequency data. Following Corsi (2009) we include realized volatility over previous daily, weekly and monthly in our daily volatility model and weekly and monthly volatility for our weekly volatility model. We find that past daily, weekly and monthly (weekly and monthly) volatility is always highly significant in our daily (weekly) volatility model. Moreover, such a model has high explanatory power for the realized volatility of Bitcoin. This result is in line with other papers that use the volatility model of Corsi (2009), but we are the first to apply this model to realized volatility of Bitcoin. Next we include several additional variables in our volatility models. Transaction volume is the only variable that has a significant relationship with realized volatility in our descriptive weekly model. On a daily scale, many significant relationships are found. Traded volume is significant for both our descriptive and predictive model. Google trends also prove significant for both predictive and descriptive models. Altogether, volatility in our models is easier explained at a daily rather than on a weekly basis.

The traded volume models show that describing traded volume is also easier on a daily scale. In the daily descriptive model, we found significant relationships between Bitcoins traded volume and Google trend data and unique addresses. On the weekly scale, realized volatility has a significant relationship to traded volume. Predicting traded volume is better done on a weekly scale as Google trend data tested significant in our weekly predictive analysis. The predictive daily and the descriptive weekly analysis proved fruitless and had no significant results.

We believe that the importance of the Bitcoin will continue to rise. It is interesting to note that during the time from when we conducted this empirical analysis until the time we finalized writing of our thesis, the Bitcoin price has skyrocketed and the Bitcoin total market value has gone from the 16 billion USD described in our article to 40 billion USD.

References

Andersen, T. G., & Bollerslev, T. (1998). Answering the skeptics: Yes, standard volatility models do provide accurate forecasts. *International economic review*, 885-905.

Andersen, T. G., Bollerslev, T., Diebold, F. X., & Labys, P. (2001). The distribution of realized exchange rate volatility. *Journal of the American statistical association*, *96*(453), 42-55.

Balcilar, M., Bouri, E., Gupta, R., & Roubaud, D. (2016). *Can Volume Predict Bitcoin Returns and Volatility? A Nonparametric Causality-in-Quantiles Approach* (No. 201662).

Birkelund, O. H., Haugom, E., Molnár, P., Opdal, M., & Westgaard, S. (2015). A comparison of implied and realized volatility in the Nordic power forward market. *Energy Economics*, *48*, 288-294.

Bouri, E., Jalkh, N., Molnár, P., & Roubaud, D. (2017). Bitcoin for energy commodities before and after the December 2013 crash: diversifier, hedge or safe haven?. *Applied Economics*, 1-11.

Bouri, E., Molnár, P., Azzi, G., Roubaud, D., & Hagfors, L. I. (2017). On the hedge and safe haven properties of Bitcoin: Is it really more than a diversifier?. *Finance Research Letters*, *20*, 192-198.

Bouoiyour, J., & Selmi, R. (2015). What Does Bitcoin Look Like?. *Annals of Economics and Finance*, *16*(2), 449-492.

Bouoiyour, J., Selmi, R., & Tiwari, A. K. (2015). Is Bitcoin business income or speculative foolery? New ideas through an improved frequency domain analysis. *Annals of Financial Economics*, *10*(01), 1550002.

Bugge, S. A., Guttormsen, H. J., Molnár, P., & Ringdal, M. (2016). Implied volatility index for the Norwegian equity market. *International Review of Financial Analysis*, *47*, 133-141.

Burniske, C., & White, A. (2016). Bitcoin: ringing the bell for a new asset class.

Cheung, Y. W. (1993). Long memory in foreign-exchange rates. *Journal of Business & Economic Statistics*, *11*(1), 93-101.

Christoffersen, P., Jacobs, K., & Mimouni, K. (2010). Volatility dynamics for the S&P500: evidence from realized volatility, daily returns, and option prices. *Review of Financial Studies*, *23*(8), 3141-3189.

Ciaian, P., Rajcaniova, M., & Kancs, D. A. (2016). The economics of BitCoin price formation. *Applied Economics*, *48*(19), 1799-1815.

Corsi, F. (2009). A Simple Approximate Long-Memory Model of Realized Volatility. *Journal of financial economics*, 7(2), 174-196.

Gordon, R. A. (1968). Issues in multiple regression. *American Journal of Sociology*, *73*(5), 592-616.

Haferkorn M., Quintana Diaz J.M. (2015) Seasonality and Interconnectivity Within Cryptocurrencies - An Analysis on the Basis of Bitcoin, Litecoin and Namecoin. In: Lugmayr A. (eds) Enterprise Applications and Services in the Finance Industry. Lecture Notes in Business Information Processing, vol 217. Springer, Cham

Haugom, E., Langeland, H., Molnár, P., & Westgaard, S. (2014). Forecasting volatility of the US oil market. *Journal of Banking & Finance*, *47*, 1-14.

Keirns, G. (March 31, 2017) *Japan's Bitcoin Law Goes Into Effect Tomorrow*, Available at: *http://www.coindesk.com/japan-bitcoin-law-effect-tomorrow/* (Accessed: May 6, 2017).

Kevin. 2017. What is Bitcoin's Correlation With Other Financial Assets?. [ONLINE] Available at: http://www.signalplot.com/what-is-bitcoins-correlation-with-other-financial-assets/. [Accessed 15 February 2017].

Kristoufek, L. (2015). What are the main drivers of the Bitcoin price? Evidence from wavelet coherence analysis. *PloS one*, *10*(4), e0123923.

Kristoufek, L. 2013. "Bitcoin Meets Google Trends and Wikipedia: Quantifying the Relationship between Phenomena of the Internet Era." Scientific Reports 3 (3415)

Lyócsa, Š., & Molnár, P. (2016). Volatility forecasting of strategically linked commodity ETFs: gold-silver. *Quantitative Finance*, *16*(12), 1809-1822.

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

O'Dwyer, K. J., & Malone, D. (2014). Bitcoin mining and its energy footprint.

Tetlock, P. C. (2007). Giving content to investor sentiment: The role of media in the stock market. *The Journal of Finance*, 62(3), 1139-1168.

Wachtel, S. B. (1942). Certain observations on seasonal movements in stock prices. *The journal of business of the University of Chicago*, *15*(2), 184-193.