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

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A R T I C L E I N F O

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A B S T R A C T

We study which variables can explain and predict the return, volatility and trading volume of Bitcoin. The considered variables are return, volatility, trading volume, transaction volume, change in the number of unique Bitcoin addresses, the VIX index and Google searches for "Bitcoin". We use realized volatility calculated from high-frequency data and find that the heterogeneous autoregressive model is suitable for Bitcoin volatility. Trading volume further improves this volatility model. The trading volume of Bitcoin can be predicted from Google searches for "Bitcoin". However, none of the considered variables can predict Bitcoin returns.

1. Introduction

Cryptocurrencies began as a fascinating idea and have grown to become a billion-dollar market. When the first Bitcoin to USD sales were made in 2009, Bitcoin was traded at 0.07 USD, whereas at the end of 2017 Bitcoin was trading at over 14000 USD. The most popular cryptocurrency is Bitcoin. Bitcoin is very different from traditional currencies. At present, many countries across the world do not yet regard Bitcoin as a legal means of payment, however there seems to be a positive trend in this respect. For example, new legislation has recently been passed in Japan that makes Bitcoin a legal form of payment there (Keirns, 2017). This is one of many factors that could contribute to a rise in Bitcoin price. However, a hack of a major Bitcoin exchange (like Mt. Gox in 2014) or a countrywide ban, and the price could plummet once again.

The determinants of Bitcoin's price, volatility, and trading volume are not yet well understood, and we thus study these in this paper. Main body of the research concludes that there is a bubble in the Bitcoin price. Bouoiyour and Selmi (2015) estimate that speculation plays a crucial role in Bitcoin price formation and conclude that Bitcoin is a speculative bubble, which is in line with research by Baek and Elbeck (2015), Cheah and Fry (2015). Similarly, Baur et al. (2018) conclude that Bitcoins are mainly used as a speculative investment. Corbet et al. (2018a) datestamp periods of bubble behavior of Bitcoin price. However, Blau (2017) finds that Bitcoin's high volatility is not caused by speculative trading.

Bitcoin has been studied from several perspectives. Feng et al. (2018) find evidence of informed trading in Bitcoin. Urquhart (2016) find that Bitcoin market is not efficient. However, Jiang et al. (2018) conclude that Bitcoin market is becoming gradually more efficient. Bitcoin has been studied also from a perspective of price clustering (Urquhart, 2017), structural breaks (Thies and Molnár, 2018), investor attention (Urquhart, 2018) and relationship to other currencies (Baumohl, 2018). For a review of Bitcoin literature see Corbet et al. (2018b).

Categorizing Bitcoin into a certain asset class is difficult. Bitcoin has been found to have a weak correlation with both risky

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financial assets and safe-haven assets (Bouri et al., 2017a; Bouri et al., 2017b; Corbet et al., 2018c), which does suggest that Bitcoin belongs to a unique and uncorrelated asset class. Kristoufek (2013) demonstrates that it is difficult to explain Bitcoin prices using standard financial theory, such as future cash flow models.

We study how volatility, return and trading volume of Bitcoin depends on other variables, such as traded volume at Bitcoin exchanges, transaction volume in Bitcoin network, the number of unique Bitcoin addresses and Google searches for the term "Bitcoin". We utilize the realized volatility of Bitcoin calculated from high frequency data.[1] We find that past realized volatility of Bitcoin predicts its future realized volatility, in accordance with the model of Corsi (2009). Moreover, trading volume improves volatility predictions. Google searches for Bitcoin predict the trading volume of Bitcoin. Bitcoin returns have a positive contemporary relationship to the number of Bitcoin addresses operational in the network. However, none of the considered variables can predict Bitcion returns, in accordance with previous findings by Kristoufek (2015), Ciaian et al. (2016) and Balcilar et al. (2017).

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

2. Data

The data used in this paper are collected from Quandl, blockchain.com, bitcoincharts.com, bitcoinity.org and Google trends. The sample spans the period between March 1, 2012 and March 19, 2017. All the data were downloaded as both daily and weekly values. The VIX index was obtained from Quandl. We used blockchain.com to download data on Bitcoin returns, Bitcoin transactions and Bitcoin addresses. Data used for the calculation of realized volatility were downloaded from bitcoinscharts.com. The trading volume of Bitcoin was obtained from bitcoinity.org. Google trends was used to download search frequency for the term "Bitcoin". Google trends is not case sensitive, it does not distinguish between "bitcoin" and "Bitcoin". Bitcoin data are available seven days a week. However, since the VIX index is not available during weekends and non-trading days, we removed these data from all the datasets that included them. The opening price on Mondays was used for all our weekly variables. Next we explain how the variables are defined.

2.1. Return

We downloaded the Bitcoin prices from blockchain.com and converted prices into returns to make them stationary. The returns are calculated as shown in Eq. (1), where subscript t stands for time. Both our daily and weekly returns are calculated in this way.

$$r_t = log(Price_t) - log(Price_{t-1}) \tag{1}$$

2.2. Volatility

To obtain as precise a measure of Bitcoin's volatility as possible, we utilize the concept of realized volatility. First, we use high-frequency data to obtain 10-minute returns. We then calculate the realized volatility according to Eq. (2), where in our case $\Delta = 10$ min, and $r_{t-j\Delta} = p_{t-j\Delta} - p_{t-(j+1)\Delta}$ defines continuously compounded 10-min returns, where p is the logarithm of Bitcoin price. Here, the subscript t indexes the day, while j indexes the time interval within day t. We calculate weekly realized volatility as a simple 5-day average of daily volatilities, see Eq. (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 a highly non-normal distribution, we transform it by taking the logarithm of it, following Liu and Maheu (2008), Chiriac and Voev (2011) and Dimp and Jank (2016). For example, the weekly realized volatility used in our analysis is calculated as (4).

$$RV_t^{'d} = \sqrt{\sum_{j=0}^{M-1} r_{t-j-\Delta}^2} \tag{2}$$

$$RV{'}_t^{w} = \frac{1}{5}(RV_t^{'d} + RV_{t-1}^{'d} + \ldots + RV_{t-4}^{'d} \tag{3}$$

$$RV_t^w = log(RV{'}_t^{w}) \tag{4}$$

2.3. Trading volume

The trading volume data were obtained individually for each of the major exchanges, and for all the smaller exchanges together as "other". The Bitcoin trading volume variable was created by simply adding the trading volume from these exchanges together. The daily trading volume was checked for seasonality, but none was detected. The trading volume variable (*Volume*) was standardized

[1] Realized volatility, introduced by Andersen and Bollerslev (1998), has previously been applied not only to stock markets (Christoffersen et al. 2010; Bugge at al. 2016) and exchange rates (Lyócsa et al., 2016) 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). Realized volatility can be conveniently modelled by a heterogeneous autoregressive model for realized volatility (Corsi, 2009).

according to Eq. (5). The *Volume* variable stands for the original data, whereas *TradingVolume* stands for standardized trading volume used in further analysis. Subscript *t* stands for time and the average volume ($\overline{Volume}$) and standard deviation of average volume σ(*Volume*) are calculated over the previous year. Both the daily and weekly trading volume variables are standardized in this way.

$$TradingVolume_t = \frac{Volume_t - \overline{Volume}}{\sigma(Volume)} \tag{5}$$

2.4. Transaction volume

Transaction volume of Bitcoin represents Bitcions exchanged for goods or services, and do not include transactions with Bitcoin exchanges. The daily transaction volume was checked for seasonality, but none was detected. The transaction volume was standardized the same way is trading volume.

2.5. Unique addresses

The Bitcoin network is made up of different addresses, each of which represents a single user's account. However, one user can have several addresses. We transform it using Eq. (7), where subscript *t* is the time index, *Adr* is the original data and *Adresses* is the variable used in further analysis. The daily unique addresses data were checked for seasonality, but none was detected. Both the daily and weekly unique addresses variables are created in this way.

$$Adresses_t = log(Adr_t) - log(Adr_{t-1}) \tag{7}$$

2.6. VIX index

The VIX index is already stationary, but to make it more comparable to our other variables we use change in the VIX index, defined by Eq. (8), where subscript *t* is the time index. The daily and weekly ΔVIX variables are both created in this way.

$$\Delta VIX_t = log(VIX_t) - log(VIX_{t-1}) \tag{8}$$

2.7. Google trends

The data on the Google search term "Bitcoin" were obtained from Google through their Trend site. Google trend data gives a normalized ratio for a search term within the specified time. The daily Google trend data was checked for seasonality, but none was detected. Following Bijl et al. (2016) and Kim et al. (2018), the original Google trend variable (*Trend*) was transformed using Eq. (9), where subscript *t* stands for time and the average ($\overline{Trend}$) and standard deviation (σ(*Trend*)) are calculated over the previous year. Both the daily and weekly Google trend variables are transformed this way.

$$GoogleTrend_t = \frac{Trend_t - \overline{Trend}}{\sigma(Trend)} \tag{9}$$

2.8. Summary statistics

The descriptive statistics for the daily data are presented in Table 1. The correlation matrix for daily data is presented in Table 2. The descriptive statistics for the weekly data are presented in Table 3. The correlation matrix for weekly data is presented in Table 4.

3. Analysis and results

Our goal is to investigate which variables can explain and predict Bitcoin returns, Bitcoin volatility and Bitcoin trading volume. The analysis is conducted on both daily and weekly data. Eq. (10) shows the model we use in our descriptive analysis, where subscript

Table 1
Descriptive statistics for daily variables.

	Mean	Median	Maximum	Minimum	Std.Dev.	Skewness	Kurtosis
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
Trading 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
ΔVIX	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 for daily variables.

	Realized volatility	Google trend	Transaction volume	Trading volume	Addresses	ΔVIX	Return
Volatility	1						
Google trend	0.00	1					
Transaction volume	0.02	−0.05	1				
Trading volume	0.03	−0.17	0.20	1			
Addresses	0.01	−0.10	0.50	0.17	1		
ΔVIX	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
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
Trading 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
ΔVIX	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 for weekly variables.

	Realized volatility	Google trend	Transaction volume	Trading volume	Addresses	ΔVIX	Return
Volatility	1						
Google trend	0.22	1					
Transaction volume	0.02	0.02	1				
Trading volume	0.18	0.01	0.13	1			
Addresses	−0.01	0.06	0.53	−0.05	1		
ΔVIX	−0.02	0.03	0.04	0.02	0.05	1	
Return	0.12	0.16	0.22	0.10	0.40	0.00	1

t is the time index and i refers to individual explanatory variables. Eq. (11) specifies the predictive regression. Every regression includes intercept, but intercept is not reported in tables with results. Statistical inference is based on robust standard errors.

$$Y_t = \alpha + \sum_{i=1}^{N} \beta_i X_{t,i} + \varepsilon_t \tag{10}$$

$$Y_t = \alpha + \sum_{i=1}^{N} \beta_i X_{t-1,i} + \varepsilon_t \tag{11}$$

The results are presented in tables. In the last column of each table we present the full regression with all the explanatory variables. In the previous columns, we present simpler regressions. In the cases of returns and trading volume, these are simple univariate regressions. However, since realized volatility is known to exhibit very high autocorrelation, all the simpler models for realized volatility include one exogenous variable and three variables capturing the high persistence of volatility – volatility from the previous day, average volatility from the previous week and average volatility from the previous month.

3.1. Returns

In the first model, we use daily data and study which variables explain daily returns of Bitcoin. The model is specified as Eq. (12) and the results are summarized in Table 5.

$$\begin{aligned} Return_t \;=\; & \alpha + \beta_1 GoogleTrend_t + \beta_2 TransactionVolume_t + \beta_3 TradingVolume_t + \beta_4 Addresses_t + \beta_5 \Delta VIX_t \\ & + \beta_6 Volatility_t + \varepsilon_t \end{aligned} \tag{12}$$

Transaction volume, trading volume, Google trends, realized volatility and the ΔVIX are all insignificant, both in the univariate regressions and in the multivariate regression. The only explanatory variable that is significant are the unique addresses used in the Bitcoin network, indicating a positive relationship between relative changes in the number of users in the Bitcoin network and Bitcoin returns. However, the R^2 of the multivariate model is 0.01, which means our model can explain only 1% of the variation in Bitcoin

Table 5
Descriptive models for Bitcoin returns estimated on daily data. Values in parentheses are standard errors. One star indicates significance at the 5% level and two stars indicate significance at the 1% level. Data span the period between March 1, 2012 and March 19, 2017.

	Dependent variable: $Return_t$						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Google $Trend_t$	0.00						−0.03
	(0.023)						(0.022)
Transaction $Volume_t$		0.01					−0.01
		(0.007)					(0.009)
Trading $Volume_t$			0.00				−0.01
			(0.003)				(0.003)
$Addresses_t$				0.03**			0.04**
				(0.011)			(0.013)
ΔVIX_t					−0.01		0.00
					(0.016)		(0.017)
$Volatility_t$						0.00	0.00
						(0.005)	(0.005)
R^2	0.00	0.00	0.00	0.01	0.00	0.00	0.01

returns.

In the second model (13), we again utilize daily data, but now study which variables can predict Bitcoin returns. The results of model (13) are summarized in Table 6.

$$Return_t = \alpha + \beta_1 GoogleTrend_{t-1} + \beta_2 TransactionVolume_{t-1} + \beta_3 TradingVolume_{t-1} + \beta_4 Addresses_{t-1} + \beta_5 \Delta VIX_{t-1} + \beta_6 Volatility_{t-1} + \varepsilon_t \quad (13)$$

Trading volume, Google trends, realized volatility and ΔVIX are all insignificant, both in the univariate regressions and in the multivariate regression. The unique address variable is significant in a univariate regression, but not in multivariate regression. This might be due to its correlation with transaction volume, as seen in Table 6. The transaction volume is significant in both univariate regression and multivariate regression. However, the R^2 is again only 0.01.

The third model utilize weekly data and studies which variables can explain Bitcoin returns. The model is specified as Eq. (14) and results are summarized in Table 7.

$$Return_t = \alpha + \beta_1 GoogleTrend_t + \beta_2 TransactionVolume_t + \beta_3 TradingVolume_t + \beta_4 Addresses_t + \beta_5 \Delta VIX_t + \beta_6 Volatility_t + \varepsilon_t \quad (14)$$

The estimated coefficients of the trading volume, realized volatility, ΔVIX and Google trend variables are not significant. Transaction volume is significant in univariate model, but not in multivariate model. The unique addresses variable is significant in both univariate and multivariate regression.

The fourth regression model specified by Eq. (15) studies which variables can predict Bitcoin returns for weekly data. The results are summarized in Table 8.

$$Return_t = \alpha + \beta_1 GoogleTrend_{t-1} + \beta_2 TransactionVolume_{t-1} + \beta_3 TradingVolume_{t-1} + \beta_4 Addresses_{t-1} + \beta_5 \Delta VIX_{t-1} + \beta_6 Volatility_{t-1} + \varepsilon_t \quad (15)$$

Table 6
Predictive models for Bitcoin returns estimated on daily data. Values in parentheses are standard errors. One star indicates significance at the 5% level and two stars indicate significance at the 1% level. Data span the period between March 1, 2012 and March 19, 2017.

	Dependent variable: $Return_t$						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Google $Trend_{t-1}$	0.00						0.01
	(0.025)						*(0.024)*
Transaction $Volume_{t-1}$		0.03**					0.02*
		(0.008)					*(0.008)*
Trading $Volume_{t-1}$			0.00				0.00
			(0.004)				*(0.004)*
$Addresses_{t-1}$				0.03**			0.02
				(0.012)			*(0.012)*
ΔVIX_{t-1}					−0.01		0.00
					(0.018)		*(0.017)*
$Volatility_{t-1}$						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

Table 7
Descriptive models for Bitcoin returns estimated on weekly data. Values in parentheses are standard errors. One star indicates significance at the 5% level and two stars indicate significance at the 1% level. Data span the period between March 1, 2012 and March 19, 2017.

	Dependent variable: Return_t						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Google Trend_t	0.10						0.08
	(0.076)						(0.066)
Transaction Volume_t		0.13**					0.01
		(0.050)					(0.036)
Trading Volume_t			0.03				0.02
			(0.029)				(0.027)
Addresses_t				0.31**			0.31**
				(0.077)			(0.077)
ΔVIX_t					0.01		0.00
					(0.103)		(0.102)
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

Table 8
Predictive models for Bitcoin returns estimated on weekly data. Values in parentheses are standard errors. One star indicates significance at the 5% level and two stars indicate significance at the 1% level. Data span the period between March 1, 2012 and March 19, 2017.

	Dependent variable: Return_t						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Google Trend_{t-1}	0.00						0.08
	(0.062)						(0.058)
Trans. Volume_{t-1}		0.01					0.05
		(0.025)					(0.054)
$\text{TradedVolume}_{t-1}$			0.00				0.01
			(0.030)				(0.027)
Addresses_{t-1}				0.03*			0.15
				(0.093)			(0.082)
ΔVIX_{t-1}					−0.01		−0.10
					(0.095)		(0.093)
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 number of unique addresses is the only significant variable. In univariate regression the unique addresses variable is significant at the 5% level, however in multivariate regression it is no longer significant. Comparing the daily and weekly predictive regressions, we see that the significance of the unique addresses variable 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.

3.2. Volatility

Our volatility models are based on the HAR-RV model proposed by Corsi (2009). The HAR-RV model successfully captures long-memory behavior of volatility and it also exhibits remarkable forecasting abilities. The simplicity of this model suits our research well. We include daily, weekly and monthly past volatility as explanatory variables in our analysis of daily data. In our analysis of weekly data, we include weekly and monthly past realized volatility. The results confirm that large part of the variation in Bitcoin's realized volatility can be explained through the lagged volatility variables.

In the first volatility model we study which variables can explain Bitcoin's daily realized volatility. The results of this model, specified by Eq. (16), are presented in Table 9.

$$\begin{aligned} Volatility_t^D \;=\; & \alpha + \beta_1 Volatility_{t-1}^D + \beta_2 Volatility_{t-1}^W + \beta_3 Volatility_{t-1}^M + \beta_4 GoogleTrend_t + \beta_5 TransactionVolume_t \\ & + \beta_6 TraingVolume_t + \beta_7 Addresses_t + \beta_8 \Delta VIX_t + \beta_9 Return_t + \varepsilon_t \end{aligned} \tag{16}$$

Using daily, weekly and monthly realized volatility as a prediction variable for the daily realized volatility yields a high R^2 value and all these variables are significant at the 1% level for all model specifications. The ΔVIX variable is not significant. The return variable is significant in restricted model presented in column 7, but not in the full model presented in column 8. The trading volume and addresses variables are significant at the 1% level for both restricted and full model specifications. Google Trends are also significant in both cases, but only at the 5% significance level. The transaction volume is significant in regression column 4, but it is no longer significant in the full model (column 8). We can see from Table 2 that transaction volume has a strong correlation with trading volume. The R^2 of the full model regression is 0.78, which means that the model can explain 78% of the variation in Bitcoin's

Table 9

Descriptive models of volatility of Bitcoin estimated on daily data. Values in parentheses are standard errors. One star indicates significance at the 5% level and two stars indicate significance at the 1% level. Data span the period between March 1, 2012 and March 19, 2017.

	Dependent variable: Volatility$_t$							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Volatility 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)
Trans. Volume$_t$			0.22**					0.06
			(0.077)					(0.070)
Trading volume$_t$				0.39**				0.39**
				(0.024)				(0.023)
Addresses$_t$					0.27**			0.12**
					(0.077)			(0.074)
ΔVIX$_t$						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

realized volatility. However, the model containing only past volatilities has an R^2 of 0.71. Moreover, the R^2 in column 3, which contains only past volatilities and trading volume, is also 0.78. This means that realized volatility is primarily explained by past realized volatility and the only other variable which significantly improves this model is trading volume.

In the next model, we study which variables can predict realized volatility of Bitcoin, again for daily data. The model is specified as follows:

$$Volatility_t^D = \alpha + \beta_1 Volatility_{t-1}^D + \beta_2 Volatility_{t-1}^W + \beta_3 Volatility_{t-1}^M + \beta_4 GoogleTrend_{t-1} + \beta_5 TransactionVolume_{t-1} + \beta_6 TradingVolume_{t-1} + \beta_7 Addresses_{t-1} + \beta_8 \Delta VIX_{t-1} + \beta_9 Return_{t-1} + \varepsilon_t \quad (17)$$

The results of this model, together with other simpler models, which each contain only one explanatory variable alongside past daily, weekly and monthly realized volatilities, are presented in Table 10.

The estimated coefficients for transaction volume, unique addresses and ΔVIX are insignificant. Trading volume, Google trends and return all have a positive relationship with future volatility of Bitcoin. However, most of the variation is still explained simply by the past volatility variables.

Next, we repeat analysis with weekly data. First, we study which variables can explain realized volatility of Bitcoin. The results of

Table 10

Predictive models of volatility of Bitcoin estimated on daily data. Values in parentheses are standard errors. One star indicates significance at the 5% level and two stars indicate significance at the 1% level. Data span the period between March 1, 2012 and March 19, 2017.

	Dependent variable: Volatility$_t$							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
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)
Trading volume$_{t-1}$				0.06**				0.06**
				(0.019)				(0.019)
Addresses$_{t-1}$					0.03			0.01
					(0.066)			(0.064)
ΔVIX$_{t-1}$						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

Table 11
Descriptive models of volatility of Bitcoin estimated on weekly data. Values in parentheses are standard errors. One star indicates significance at the 5% level and two stars indicate significance at the 1% level. Data span the period between March 1, 2012 and March 19, 2017.

	Dependent variable: Volatility_t (1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
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)
Trading volume_t				0.01				0.02
				(0.052)				(0.053)
Addresses_t					−0.13			−0.31
					(0.149)			(0.195)
ΔVIX_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 model (18) are presented in Table 11.

$$\begin{aligned} Volatility_t^W \; &= \; \alpha + \beta_1 Volatility_{t-1}^W + \beta_2 Volatility_{t-1}^M + \beta_3 GoogleTrend_t + \beta_4 TransactionVolume_t \\ &+ \beta_5 TradingVolume_t + \beta_6 Addresses_t + \beta_7 \Delta VIX_t + \beta_8 Return_t + \varepsilon_t \end{aligned} \tag{18}$$

The volatility over the previous week and month are once again significant. The Google trends, returns, trading volume, unique addresses and ΔVIX are not significant in explaining the weekly realized volatility. The only significant result found for any of the non-volatility variables is for transaction volume in the full model (column 8). Howver, the R^2 of this model is 0.70, which is only marginally higher than R^2 of the basic model which includes only past volatilities.

Next, we study which variables can predict the weekly realized volatility of Bitcoin. The results of model (19) are shown in Table 12.

$$\begin{aligned} Volatility_t^W \; &= \; \alpha + \beta_1 Volatility_{t-1}^W + \beta_2 Volatility_{t-1}^M + \beta_3 GoogleTrend_{t-1} + \beta_4 TransactionVolume_{t-1} \\ &+ \beta_5 TradingVolume_{t-1} + \beta_6 Adresses_{t-1} + \beta_7 \Delta VIX_{t-1} + \beta_8 Return_{t-1} + \varepsilon_t \end{aligned} \tag{19}$$

As previously, the volatility over the previous week and month are significant. The Google trends, returns, transaction volume, trading volume, unique addresses and ΔVIX variables are insignificant in all the considered models. We still see that most of the variation in volatility can be explained by the volatility variables.

Table 12
Predictive models of volatility of Bitcoin estimated on weekly data. Values in parentheses are standard errors. One star indicates significance at the 5% level and two stars indicate significance at the 1% level. Data span the period between March 1, 2012 and March 19, 2017.

	Dependent variable: Volatility_t (1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
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 $\text{Trend}_{(t-1)}$		0.06						0.09
		(0.096)						(0.094)
Transaction Volume_{t-1}			−0.05					−0.12
			(0.090)					(0.108)
Trading volume_{t-1}				0.11				0.11
				(0.063)				(0.063)
Addresses_{t-1}					0.12			0.22
					(0.152)			(0.185)
ΔVIX_{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

Table 13
Descriptive models of Bitcoin trading volume estimated on daily data. Values in parentheses are standard errors. One star indicates significance at the 5% level and two stars indicate significance at the 1% level. Data span the period between March 1, 2012 and March 19, 2017.

	Dependent variable: Trading Volume$_t$						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Google trend$_t$	−1.13**						−1.01**
	(0.241)						(0.215)
Addresses$_t$		0.69**					0.42**
		(0.155)					(0.128)
ΔVIX$_t$			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

3.3. Trading volume

Next, we study which variables can explain Bitcoin's daily trading volume for daily data. The results of this model, specified as Eq. (19), are presented in Table 13.

$$TradingVolume_t = \alpha + \beta_1 GoogleTrend_t + \beta_2 TransactionVolume_t + \beta_3 Addresses_t + \beta_4 \Delta VIX_t + \beta_5 Return_t + \beta_6 Volatility_t + \varepsilon_t \tag{19}$$

Returns and ΔVIX are insignificant. The transaction volume variable is significant in univariate regression, but not in multivariate regression. The unique addresses, Google trends and realized volatility are significant in both univariate and multivariate regressions. Unique addresses have positive association with trading volume, whereas Google trends and realized volatility have negative association.

Next, we study whether the same variables can predict trading volume of Bitcoin in daily data. We study the determinants of the daily trading volume of Bitcoin in the following model:

$$TradingVolume_t = \alpha + \beta_1 GoogleTrend_{t-1} + \beta_2 TransactionVolume_{t-1} + \beta_3 Addresses_{t-1} + \beta_4 \Delta VIX_{t-1} + \beta_5 Return_{t-1} + \beta_6 Volatility_{t-1} + \varepsilon_t \tag{20}$$

The results for model (20) are shown in Table 14. All the considered variables are insignificant and the R^2 of this model is only 0.01.

Next, we repeat the analysis using weekly data. First, we study contemporary relationship. The model is specified as follows:

$$TradingVolume_t = \alpha + \beta_1 GoogleTrend_t + \beta_2 TransactionVolume_t + \beta_3 Addresses_t + \beta_4 \Delta VIX_t + \beta_5 r_t + \beta_6 Volatility_t + \varepsilon_t \tag{21}$$

The results for model (21) are shown in Table 15. Only the realized volatility variable is significant. However, the R^2 of this model

Table 14
Predictive models of Bitcoin trading volume estimated on daily data. Values in parentheses are standard errors. One star indicates significance at the 5% level and two stars indicate significance at the 1% level. Data span the period between March 1, 2012 and March 19, 2017.

	Dependent variable: Trading Volume$_t$						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Google trend$_{t-1}$	0.25						−0.03
	(0.271)						(0.232)
Addresses$_{t-1}$		−0.12					0.02
		(0.094)					(0.155)
ΔVIX$_{t-1}$			0.12				0.38
			(0.171)				(0.171)
Trans. 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

Table 15
Descriptive models of Bitcoin trading volume estimated on weekly data. Values in parentheses are standard errors. One star indicates significance at the 5% level and two stars indicate significance at the 1% level. Data span the period between March 1, 2012 and March 19, 2017.

	Dependent variable: Trading Volume$_t$						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Google trend$_t$	0.01						−0.04
	(0.107)						(0.107)
Addresses$_t$		−0.10					0.04
		(0.162)					(0.209)
ΔVIX$_t$			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

Table 16
Predictive models of Bitcoin trading volume estimated on weekly data. Values in parentheses are standard errors. One star indicates significance at the 5% level and two stars indicate significance at the 1% level. Data span the period between March 1, 2012 and March 19, 2017.

	Dependent variable: Trading Volume$_t$						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Google trend$_{t-1}$	0.57**						−1.00**
	(0.141)						(0.109)
Addresses$_{t-1}$		0.12					0.20
		(0.169)					(0.193)
ΔVIX$_{t-1}$			−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

is only 0.03, which means our model can explain 3% of variation in the trading volume of Bitcoin.

In our final model, we study which variables can predict Bitcoin's trading volume in weekly data. The model is specified in Eq. (22) and the results for model (22) are shown in Table 16.

$$TradingVolume_t = \alpha + \beta_1 GoogleTrend_{t-1} + \beta_2 TransactionVolume_{t-1} + \beta_3 Addresses_{t-1} \\ + \beta_4 \Delta VIX_{t-1} + \beta_5 Return_{t-1} + \beta_6 Volatility_{t-1} + \varepsilon_t \tag{22}$$

The only variables significant in the full model (column 7) are Google trends and transaction volume. Other things being equal, high transaction volume predicts high trading volume and high Google searches predict low trading volume.

4. Conclusion

Bitcoin's popularity, and in turn its value, have been changing tremendously, yet our understanding of the factors that determine Bitcoin's trading activity is rather limited. In this paper, we contribute to this understanding by studying which variables are useful in explaining and predicting the returns, volatility and trading volume of Bitcoin.

We began by analyzing possible determinants of Bitcoin returns. We found that changes in the number of unique addresses used in the Bitcoin network are positively related with Bitcoin returns on both weekly and daily time horizons. Bitcoin's transaction volume predicts (to a small extend) its daily returns, but not weekly returns. From a practical perspective, most of the variation in Bitcoin's returns remains unexplained. In this respect, Bitcoin resembles other financial assets, for which price changes are difficult to predict.

In our analysis of Bitcoin's volatility, we utilized realized volatility calculated from high-frequency data. Following Corsi (2009), we included past daily, weekly and monthly volatility in our volatility models and found that past volatilities are always highly significant. Moreover, these models have high explanatory power. This result is in line with previous literature about volatility modeling. Next, we included several additional variables in our volatility models. On a daily scale, we found that daily volatility is correlated with and can be predicted by the trading volume of Bitcoin. However, none of the variables can predict weekly volatility.

The trading volume of Bitcoin is correlated with several of the considered variables. However, only two variables are predictors of trading volume. These are Google searches for the term “Bitcoin” and the transaction volume in the Bitcoin network.

From a practical perspective, market participants are primarily interested in predicting price changes, and secondary interested in predicting volatility. Changes in Bitcoin price are unpredictable and realized volatility is highly predictable from its past values. With this respect, Bitcoin is like other financial assets. However, additional finding, which is not usually reported for other financial assets, is that the trading volume of Bitcoin improved predictions of Bitcoin volatility.

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