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What causes the attention of Bitcoin?

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HIGHLIGHTS

- We study the attention of Bitcoin by employing *Google Trends* data.
- We find that realized volatility and volume significantly influence next day's attention.
- However attention offers no significant predictive power for realized volatility or returns.
- Therefore the attention of Bitcoin is significantly influenced by the previous day's high realized volatility and volume.

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ABSTRACT

Bitcoin has received enormous attention both by the media and investors alike. But why has Bitcoin received such attention? This paper answers this question by examining the relationship between investor attention and Bitcoin fundamentals and finds that realized volatility and volume are both significant drivers of next day attention of Bitcoin.

1. Introduction

In recent times, Bitcoin has been the subject of much attention, both by the media and investors. This surge in attention can be attributed to its innovative features, simplicity, transparency and its increasing popularity (Urquhart, 2016), but it also poses great challenges and opportunities for policy makers, economists, entrepreneurs, and consumers. The academic literature on Bitcoin is growing, with Cheah and Fry (2015) and Corbet et al. (2018) both documenting bubbles in the Bitcoin price, Urquhart (2016) and Bariviera (2017) and Nadarajah and Chu (2017) all confirm the inefficiency of Bitcoin, Katsiampa (2017) showing that the best volatility model for Bitcoin is the AR-CGARCH model, Urquhart (2017) reporting price clustering in Bitcoin, Phillip et al. (2018) showing that Bitcoin has many diverse stylized facts including long memory and heteroskedasticity while Baur et al. (2018) show that Bitcoin is a speculative investment and not an alternative currency or medium of exchange.

But a question yet to be answered in the literature is what factors have driven the attention of Bitcoin. To examine this, we employ *Google Trends* data as a proxy for investor attention to determine whether returns, realized volatility or volume are significant drivers of the attention of Bitcoin. We find that realized volatility and volume are significant drivers of next day investor attention but investor attention offers no significant predictive power in forecasting realized volatility, volume or returns.

2. Data and methodology

We obtain attention data from *Google Trends*[1] for the keyword "Bitcoin" and study the period 1st August 2010 to 31st July 2017. This sample period is chosen since before August 2010, the search volume is very low and many days consist of zero searches for "Bitcoin". Coincidentally, it also provides us with 7 full year of data which helps avoid any seasonality issues. The volume measure is based on the number of searches which were submitted within the

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[1] Source: *Google Trends* (www.google.com/trends).

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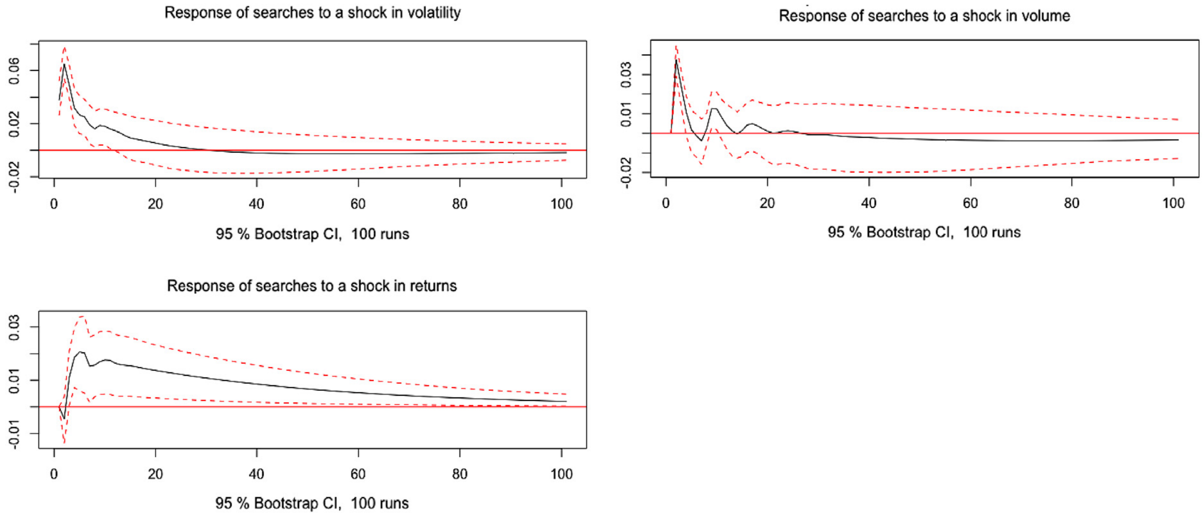

Fig. 1. Impulse response functions for searches after a shock in volatility, volume and returns.

Table 1
This table shows the top ten search terms that are most correlated with the search term ‘bitcoin’ during the sample period January 2010 to July 2017 on a weekly frequency. The second column provides the correlation coefficient from Google Correlate while the third column shows the search volume relative to the search volume for ‘bitcoin’.

Rank	Correlation	Relative volume (%)	Search term
1	0.9784	76.43%	bitcoin rate
2	0.9754	68.76%	current bitcoin
3	0.9746	83.89%	how bitcoin works
4	0.9740	77.81%	bitcoin usd
5	0.9736	71.63%	mining bitcoin
6	0.9732	78.20%	bitcoin trading
7	0.9694	93.71%	bitcoin currency
8	0.9693	81.73%	bitcoin?
9	0.9672	82.11%	bitcoin dollar
10	0.9666	60.32%	current bitcoin value

USA. Since the data is relative in nature, we follow Dimpfl and Jank (2016) and standardize the search queries such that the average search frequency over the sample period equals one.

We use the search term “Bitcoin” to measure retail investors’ attention to this index, since we find that this short name is the most widely used search term when investors are interested in bitcoin. Table 1 provides an overview of the search terms that have the highest correlation with the term “Bitcoin” according to Google Correlate.[2] This table compares the level of search volume relative to the search term “Bitcoin” and we find that a number of different words have a very strong correlation with “Bitcoin”. However, all of the highly correlated search terms have a lower search volume than “Bitcoin”, and therefore do not add further information beyond our initial search. Seasonality is also an issue with search query data and therefore we follow Da et al. (2014) and regress the search query data on day-of-the-week and month-of-the-year dummies, however there is little evidence of significant seasonality pattern for trading days.[3]

We focus on the Bitstamp exchange as it is the most liquid and popular Bitcoin exchange in the US. Tick data is downloaded from www.bitcoincharts.com where we aggregate the data to the 5-min level to construct a time series of daily realized volatility RV_t as introduced by Anderson et al. (2003) such that:

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

where $r_{t,j}^2$ is the squared intraday log-price changes of the index and day t during interval j and n is the number of such intraday return intervals. We compute these price changes over 5 min intervals in order to circumvent the well documented microstructure effects (see Anderson et al., 2003). To obtain daily volume and returns data, we aggregate the tick data to the daily level.[4]

Table 2 reports the descriptive statistics for the standardized search queries data, realized volatility, logarithmic trading volume as well as logarithmic returns. The standardized search queries has a maximum value of 3.67 and a minimum value of 0.07 indicating the large variation in the search query data. However, there is large positive skewness and excess kurtosis but when we take the logarithm of the search queries, we find that the excess skewness and kurtosis is less pronounced. The mean of the realized volatility is −6.36, with quite a large standard deviation of 1.24 as well as negative skewness. The mean logarithmic volume is 8.89 which indicates the liquidity of the Bitcoin market. Finally the returns show similar statistics as we would expect, namely positive mean return, negative skewness and a leptokurtic distribution.

In order to study the dynamics between search queries, realized volatility, trading volume and returns, we estimate vector autoregressive (VAR) models. Let x_t be a vector that contains the variables of interest, then a VAR(k) reads as follows:

$$x_t = c + \sum_{j=1}^{k} \beta_j x_{t-j} + \epsilon_t \tag{2}$$

where c is a vector of constants and ϵ_t is a vector of independent white noise innovations. The lag-length is determined using the Schwarz Bayesian information criterion. Model 1 investigates the dynamics between realized volatility and search queries ($x_t = logSQ_t \ logRV$), while Model 2 sheds light on the interaction between search queries and trading volume ($x_t = logSQ_t \ logVol$) and

2 Source: *Google Correlate* (www.google.com/trends/correlate/).

3 As a robustness check, we filter our original series by taking the residual obtained from the regression on the day-of-the-week and month-of-the-year dummies. We then employ these filtered returns in our subsequent analysis and find qualitatively very similar results, which are available upon request from the corresponding author.

4 We take logarithmic volume and returns in order to reduce skewness and kurtosis.

Table 2
This table reports the descriptive statistics of the standardized search queries, as well as the logarithmic search queries, logarithmic realized volatility, logarithmic volume and logarithmic returns.

	Mean	Std.Dev	Max	Min	Skew	Kurtosis
stan-SQ	1.0000	0.5661	3.6724	0.0735	1.3353	3.7412
log-SQ	−0.1796	0.6522	1.3009	−2.6112	−0.8797	0.8861
log-RV	−6.3619	1.2372	−0.0628	−9.3531	−0.1770	0.1973
log-Volume	8.8912	0.9267	11.8146	5.3762	0.7533	1.2581
log-Returns	0.0032	004916	0.3718	−0.8219	−3.0639	3.9501

Table 3
This table displays the estimation results of three vector autoregressive models for log realized volatility ($log - RV$), log search queries ($log - SQ$) and log trading volume ($log - VO$) for Bitcoin. Model 1 considers the dynamics between log-RV and log-SQ and model 2 between log-SQ and log-VO, while Model 3 comprises of all variables. Panel A reports the coefficient estimates while Panel B provides the test statistics of the Granger causality test.

Panel A: VAR Estimation

	Model 1		Model 2		Model 3	
	RV_t	SQ_t	SQ_t	VO_t	R_t	SQ_t
SQ_{t-1}	0.1625*	0.7352***	0.7411***	0.1152	−0.0071	0.7899***
SQ_{t-2}	−0.1960*	0.0292	0.0319	−0.1013	0.0058	0.0075
SQ_{t-3}	−0.0065	0.0189	0.0264	−0.0482	−0.0072	0.0163
SQ_{t-4}	−0.1388	−0.0019	0.0103	−0.0591	0.0181**	0.0064
SQ_{t-5}	0.2456**	0.0803***	0.0739**	0.0871	0.0141**	0.1443***
SQ_{t-6}	0.01676	0.0509*	0.0396	0.0583		
SQ_{t-7}	−0.0789	0.0576**	0.0452*	−0.0702		
RV_{t-1}	0.5858***	0.0508***				
RV_{t-2}	0.0271	−0.0303***				
RV_{t-3}	0.0647	−0.0106				
RV_{t-4}	0.0650**	0.0038				
RV_{t-5}	−0.0186	−0.0022				
RV_{t-6}	0.0570**	−0.0101				
RV_{t-7}	0.0599**	−0.0085				
VO_{t-1}			0.0686***	0.4651***		
VO_{t-2}			−0.0392***	0.0240		
VO_{t-3}			−0.0139	0.0444		
VO_{t-4}			−0.0098	−0.0591		
VO_{t-5}			−0.0048	0.0871		
VO_{t-6}			−0.0049	0.1114***		
VO_{t-7}			0.0022	0.2134***		
R_{t-1}					0.0350	−0.0946
R_{t-2}					−0.1074***	0.3086***
R_{t-3}					−0.0335	0.1806*
R_{t-4}					0.0531**	0.1460
R_{t-5}					0.1051***	0.1070
Constant	−0.8333***	−0.0581***	−0.0058	0.7110***	0.0020	−0.0279**

Panel B: Granger Causality Test

RV does not Granger Cause SQ	11.05***	SQ does not Granger Cause RV	1.56
Volume does not Granger Cause SQ	11.63***	SQ does not Granger Cause Volume	1.04
Returns does not Granger Cause SQ	3.62***	SQ does not Granger Cause Returns	2.60**

*** Significance at the 1% level.
** Significance at the 5% level.
* Significance at the 10% level.

Model 3 examines the relationship between search queries and returns ($x_t = logSQ_t\ logRet$).

3. Empirical results

3.1. Vector autoregression and impulse response results

Table 3 displays the results of the three VAR models where the coefficient estimates are presented in Panel A, and the results of the Granger causality test are shown in Panel B. In Model 1, we find significant estimates of the autoregressive parameters for the realized volatility for lags 1, 4, 6 and 7 while search queries also show significant autoregressive terms for lags 1, 5 and 7 respectively. The estimation results also reveal that past search queries does not significantly influence realized volatility as the coefficient is only significant at the 10% level. This is also supported by the Granger causality test in Panel B which fails to reject the null hypothesis that search queries cause realized volatility. However we do find that past volatility significantly influences search queries at lag 1 indicating that an increase in volatility will lead to an increase in search queries the following day. Furthermore, the Granger causality test indicates that past volatility provides significant information about future search queries. Model 2 analysis the interaction of trading volume and search queries and similar to Model 1, the autoregressive search query term is significant at lag 1. We also find that past volume provides significant information about future search queries. This suggests that when trading volume is high for Bitcoin, more information is sought from Google the following day. The Granger causality test also shows that trading volume Granger-causes search queries for Bitcoin. The interaction between returns and search queries is reported in Model 3 and interestingly shows that returns at lag 2 significantly provides information about search queries. This suggests that when returns of Bitcoin are high, the number of search queries increases but with a two day

Table 4
This table displays the estimation results of three vector autoregressive models for log realized volatility ($log - RV$), log search queries ($log - SQ$) and log trading volume ($log - VO$) for Bitcoin. Model 1 considers the dynamics between log-RV and log-SQ and model 2 between log-SQ and log-VO, while Model 3 comprises of all variables. Panel A reports the coefficient estimates while Panel B provides the test statistics of the Granger causality test.

Panel A: VAR Estimation

	Model 1		Model 2		Model 3	
	RV_t	SQ_t	SQ_t	VO_t	R_t	SQ_t
SQ_{t-1}	0.3522*	0.7931	0.7922***	0.2246	−0.0142	0.7971***
SQ_{t-2}	−0.3794	0.0522	0.0552	−0.2309***	−0.0007	0.0520
SQ_{t-3}	0.0963	−0.0326	−0.0239	0.0635	−0.0158	−0.0300
SQ_{t-4}	−0.2431	−0.0114	−0.0167	0.0294	0.0306*	−0.0075
SQ_{t-5}	0.2952	0.1493***	0.1217**	0.0772	−0.0077	0.146***
SQ_{t-6}			0.0011	−0.1230		
SQ_{t-7}			0.0170	0.0213		
RV_{t-1}	0.4969***	0.0160				
RV_{t-2}	0.0287	−0.0112				
RV_{t-3}	0.0931*	0.0029				
RV_{t-4}	0.0636	−0.0029				
RV_{t-5}	0.0412	−0.0039				
RV_{t-6}						
RV_{t-7}						
VO_{t-1}			0.0257	0.2625***		
VO_{t-2}			−0.0296**	0.0265		
VO_{t-3}			0.00487	−0.0374		
VO_{t-4}			−0.0146	0.0200		
VO_{t-5}			−0.0037	−0.0307		
VO_{t-6}			−0.0028	0.1227***		
VO_{t-7}			0.0175	0.2749***		
R_{t-1}					0.0662	0.0179
R_{t-2}					−0.174***	0.2248
R_{t-3}					−0.0620	0.2794
R_{t-4}					0.0254	0.1313
R_{t-5}					0.1614***	0.1168
Constant	−1.5143***	−0.0054			0.0059	−0.0139

Panel B: Granger Causality Test

RV does not Granger Cause SQ	0.41	SQ does not Granger Cause RV	1.64
Volume does not Granger Cause SQ	1.23	SQ does not Granger Cause Volume	0.85
Returns does not Granger Cause SQ	1.06	SQ does not Granger Cause Returns	1.73

*** Significance at the 1% level.
** Significance at the 5% level.
* Significance at the 10% level.

delay. There is also is no evidence of a significant autoregressive return term for Bitcoin. Also, Panel B shows that we can reject the null hypothesis that returns do not Granger cause search queries indicating that returns do Granger cause search queries.

To further examine what influences the attention of Bitcoin, Fig. 1 presents the impulse response functions, where we employ the Cholesky decomposition. We can see that after a volatility, volume or returns shock, attention is elevated for a number of days, but is long lasting after a shock in returns.

3.2. Subsample results

So far, our analysis has suggested that realized volatility, volume and returns all significantly influence future search queries. However this finding may not be stable over time and therefore we split our search queries data into two subsamples. To choose the split point, we employ the Bai and Perron (2003) test and select the breakpoint with the greatest significance which corresponds to 28th October 2013. Therefore our first subsample covers 1st July 2012 to 27th October 2013 while the second subsample examines the period 28th October 2013 to 31st July 2017. The first subsample results are reported in Table 4 where we find that realized volatility has no significant influence on search queries. We also find that at lag 1, volume offers no significant influence on search queries although there is a negative significant effect at lag 2 indicating that lower volume one day influence search queries two days later. Also, returns have no significant influence on search queries at any lag, which indicates that our variables have no influence on future search queries. This is supported by the Granger causality tests which all fail to reject the null hypothesis in each case. Therefore from 1st July 2012 to 27th October 2013, realized volatility, volume and returns have no significant influence on future search queries. Table 5 presents the VAR results for the second subsample and shows that realized volatility significantly influences future search queries at lags 1, 2, 3 and 6, while volume influences future search queries at lags 1, 2 and 3. We also find that returns at lag 2 significantly influence search queries indicating that there is a clear change in behaviour of our results over subsample. Since 28th October 2013, all three variables have been influencing search queries but not before. We also find, consistent with the full sample analysis, that search queries do not offer any significant predictive power in forecasting realized volatility, volume or returns.

4. Conclusion

This papers utilities *Google Trends* search queries to examine what drives the attention of Bitcoin. We find that previous day volatility and volume are significant drivers of attention of Bitcoin, as well as two days previous returns. However after splitting our data into two subsamples, we find that this is only the case from October 2013 and therefore our results indicate that investors are attracted to Bitcoin after large increases in volatility and trading volume of Bitcoin.

Table 5
This table displays the estimation results of three vector autoregressive models for log realized volatility ($log-RV$), log search queries ($log-SQ$) and log trading volume ($log-VO$) for Bitcoin. Model 1 considers the dynamics between log-RV and log-SQ and model 2 between log-SQ and log-VO, while Model 3 comprises of all variables. Panel A reports the coefficient estimates while Panel B provides the test statistics of the Granger causality test.

Panel A: VAR Estimation

	Model 1		Model 2		Model 3	
	RV_t	SQ_t	SQ_t	VO_t	R_t	SQ_t
SQ_{t-1}	−0.0110	0.6856***	0.6790***	0.0725	0.0005	0.7374***
SQ_{t-2}	−0.0435	0.0423	0.0319	−0.0008	0.0085	−0.0191
SQ_{t-3}	−0.1009	−0.0258	0.0429	−0.173*	−0.0003	0.0344
SQ_{t-4}	−0.0777	0.0246	0.0410	−0.097	0.0067	0.0168
SQ_{t-5}	0.1355	0.0676	0.0597*	0.1132	−0.0096	0.0395
SQ_{t-6}	0.0784	0.1107***	0.0484	0.1959*	−0.0065	0.0591*
SQ_{t-7}			0.0545**	−0.1253	−0.0024	0.0862***
RV_{t-1}	0.6596***	0.0805***				
RV_{t-2}	0.0227	−0.4391***				
RV_{t-3}	0.0401	−0.0216**				
RV_{t-4}	0.0855**	0.00976				
RV_{t-5}	−0.0320	−0.1059				
RV_{t-6}	0.0881***	−0.0220***				
RV_{t-7}						
VO_{t-1}			0.0909***	0.5361***		
VO_{t-2}			−0.0371***	−0.0153		
VO_{t-3}			−0.0211**	0.0768**		
VO_{t-4}			−0.0092	0.0783**		
VO_{t-5}			−0.0132	−0.0351		
VO_{t-6}			−0.0048	0.0857***		
VO_{t-7}			−0.0076	0.1550***		
R_{t-1}					−0.0150	−0.1324
R_{t-2}					−0.0585**	0.3811***
R_{t-3}					−0.0015	0.1379
R_{t-4}					0.0759***	0.2129*
R_{t-5}					0.0479*	0.1700
R_{t-6}					0.0789***	0.0758
R_{t-7}					0.0389	0.1967*
Constant	−0.0054	−0.7893***	0.0297	1.129***	−0.0004	−0.0009

Panel B: Granger Causality Test

RV does not Granger Cause SQ	23.63**	SQ does not Granger Cause RV	0.90
Volume does not Granger Cause SQ	15.58***	SQ does not Granger Cause Volume	1.88*
Returns does not Granger Cause SQ	3.05***	SQ does not Granger Cause Returns	1.49

*** Significance at the 1% level.

** Significance at the 5% level.

* Significance at the 10% level.

References

Anderson, T.G., Bollerslev, T., Diebold, F.X., Laybs, P., 2003. Modeling and forecasting realized volatility. Econometrica 71, 579–625.

Bai, J., Perron, P., 2003. Computation and analysis of multiple structural change models. J. Appl. Econometrics 18, 1–22.

Bariviera, A.F., 2017. The inefficiency of Bitcoin revisited: A dynamic approach. Econom. Lett. 161, 1–4.

Baur, D., Hong, K., Lee, A.D., 2018. Bitcoin: Medium of exchange or speculative assets? J. Int. Financ. Markets Inst. Money (forthcoming).

Cheah, E.T., Fry, J., 2015. Speculative bubbles in Bitcoin markets? An empirical investigation into the fundamental value of bitcoin. Econom. Lett. 130, 32–36.

Corbet, S., Lucey, B., Yarovaya, L., 2018. Datestamping the Bitcoin and Ethereum bubbles. Finance Res. Lett. (forthcoming).

Da, Z., Engelberg, J., Gao, P., 2014. The sum of all FEARS investor sentiment and asset prices. Rev. Financ. Stud. 28, 1–32.

Dimpfl, T., Jank, S., 2016. Can internet search queries help to predict stock market volatility? Eur. Financ. Manag. 22, 171–192.

Katsiampa, P., 2017. Volatility estimation for Bitcoin: A comparison of GARCH models. Econom. Lett. 158, 3–6.

Nadarajah, S., Chu, J., 2017. On the inefficiency of Bitcoin. Econom. Lett. 150, 6–9.

Phillip, A., Chan, J., Peiris, S., 2018. A new look at Cryptocurrencies. Econom. Lett. 163, 6–9.

Urquhart, A., 2016. The inefficiency of Bitcoin. Econom. Lett. 148, 80–82.

Urquhart, A., 2017. Price clustering in Bitcoin. Econom. Lett. 159, 145–148.