

Information demand and cryptocurrency market activity

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Abstract:

This paper studies the relationship between information demand measured by Google search volume index, price returns, and trading volume for five major cryptocurrencies. We find that past information demand flows significantly influence the volume of all cryptocurrencies except for Litecoin. Moreover, trading volumes are found to Granger cause the information demand flows of Bitcoin, Ripple, and Litecoin, while previous day's returns significantly influence the information demand flows.

Keywords: Information demand flows, Bitcoin, Cryptocurrency, Volume, VAR

1. Introduction

The importance of information to market activity has been highlighted in several studies. Information is the most valued asset in financial markets (Vlastakis and Markellos, 2012). For this reason, there has been increased academic interest in the relationship between information demand and market activity in different financial markets (see, e.g., Vlastakis and Markellos, 2012; Vozlyublennaia, 2014; Goddard et al., 2015; Chronopoulos et al., 2018). Nevertheless, the relationship between information demand and market activity in cryptocurrency markets still remains underexplored, despite the fact that the literature on cryptocurrencies has rapidly emerged. Among the few studies that have analysed cryptocurrency search queries are those of Ciaian et al. (2016), Urquhart (2018), and Shen et al. (2019). However, all of these studies considered only Bitcoin excluding other cryptocurrencies despite the fact that altcoins have been gaining in popularity and market share.¹

Consequently, this paper studies the relationship between information demand, returns, and trading volume for five major cryptocurrencies. Our study contributes to the growing literature on cryptocurrencies as well as on the relationship between information demand and market activity. To the best of the authors' knowledge, this is the first study to examine such a relationship for altcoins.

¹ It is worth mentioning that while Bitcoin's market share was about 95% in May 2013, it has significantly dropped to 55% (Coinmarketcap.com accessed on 12th June 2019).

2. Data and methodology

In this study, we consider the five largest cryptocurrencies in terms of market capitalisation². Data on cryptocurrencies' price and volume are collected from the earliest date for which both price and volume data are available at https://coinmarketcap.com/coins/ to 20th January 2019. The dataset therefore comprises daily closing prices and volumes for Bitcoin (from 27th December 2013), Ripple (from 27th December 2013), Ether (from 7th August 2015), Stellar (from 5th August 2014), and Litecoin (from 27th December 2013). Similar to Urquhart (2018), daily data about information demand flows are sourced from Google Trends using the name of the cryptocurrency as the keyword.

In order to explore the dynamics between our variables, we employ the Vector Autoregressive (VAR) model, expressed as

$$y_t = c + \sum_{i=1}^p \beta_i y_{t-i} + \varepsilon_t,$$

where y_t is a 3 × 1 vector containing the three variables of our interest (i.e., returns³, logarithmic volumes, and standardised information demand flows⁴), *c* denotes a 3 × 1 vector of constants, and ε_t represents a 3 × 1 vector of independent white noise errors. The lag order *p* is determined using the Schwarz information criterion allowing up to ten lags. In order to investigate possible causal relationships between information demand, volume, and returns, we also employ Granger causality tests.

3. Empirical results

3.1 Data analysis

Summary statistics for our variables can be found in Table 1. We notice that all the cryptocurrencies have a positive mean return, while Bitcoin has the smallest standard deviation and Stellar the highest.⁵

² As of 21st January 2019.

³ As standard, we compute logarithmic returns.

⁴ Standardised as (*value – mean*)/*standard deviation*.

⁵ In unreported results due to space constraints, we ensure that our variables are stationary through the Phillips-Perron test. These results are available upon request from the corresponding author.

3.2 Entire sample period analysis

In Table 3, Panel A presents the estimation results of the VAR models for each cryptocurrency over the entire sample period, while Panel B provides the corresponding Granger causality test statistics. Unlike the volume and information demand equations, in the return equation we find little evidence of autocorrelation of returns. With the exception of Ether, we further find little evidence that previous day's volume or information demand predicts returns, where these findings are supported by the Granger causality results in Panel B. For the volume equation, we find significant evidence that previous day's information demand predicts volume for all altcoins, while previous day's information demand predicts volume for all altcoins, while previous day's demand. Also, previous day's volume predicts information demand for all cryptocurrencies except Stellar.

3.3 Sub-sample analysis

Next, we performed the multiple unknown structural breakpoint test of Bai and Perron (1998) and found that Bitcoin and Ether exhibit one breakpoint each on 17th December 2017 and 14th January 2018, respectively. Consequently, we re-performed our analysis in the sub-samples for Bitcoin and Ether, the results of which can be found in Table 3. Overall, we notice some discrepancies when comparing the two sub-samples not only in the magnitude, sign, and significance of the different coefficients (Panel A) but also in the Granger causality results (Panel B).

Regarding Bitcoin, similar to the entire sample, information demand does not have a significant effect in the returns in any sub-sample. Nevertheless, previous day's returns are now found to have a significant impact on Bitcoin's information demand in both sub-samples, although in the first sub-sample this is true only at the 10% level of significance. Furthermore, similar to the entire sample, past volume significantly influences current information demand in both sub-samples, whereas previous information demand flows now have a significant impact on current trading volume levels only in the first sub-sample. All these findings are in agreement with the Granger causality results. The Granger causality results further reveal significant bidirectional causality between returns and volume but only in the first sub-sample.

As for Ether, in the return equation we find a significant estimate of the autoregressive parameter for information demand for lag 1 at the 5% level in the sub-sample before the breakpoint but not in the second sub-sample. It is worth mentioning that information demand flows were found to Granger-cause returns in the entire sample period as well. Moreover, similar to the entire period, past returns significantly influence the current information demand in both sub-sample periods, as well as the current trading volume but only in the first sub-sample. We also notice that, similar to the entire period, past information demand significantly affects current trading volume in both sub-periods. All these findings are in accordance with the Granger causality results. On the other hand, similar to the entire sample, volume does not Granger-cause information demand in any sub-sample. However, unlike the results for the entire sample period, the Granger causality results for the sub-samples suggest that volume does not Granger cause the returns in any of the two sub-samples.

4. Conclusion

This paper examined the relationship between information demand, returns, and trading volumes for five cryptocurrencies by employing the VAR model and the Granger causality test. According to the results over the entire sample period, previous day's returns significantly influence the information demand flows of all cryptocurrencies apart from Bitcoin and previous day's volume significantly affects the information demand of all cryptocurrencies except for Stellar. On the other hand, information demand flows at lags 1 or 2 significantly influence the volume of all cryptocurrencies except for Litecoin but the returns of only Ether.

However, after testing for structural breaks and separating the sample period of Bitcoin and Ether in two, we found that returns influence information demand in both subsamples of both cryptocurrencies, with the causality being stronger in the sub-sample after the breakpoint, though. Moreover, volume Granger-causes information demand in both sub-samples of Bitcoin but not in any of the two sub-samples of Ether. Finally, it was shown that past information demand flows influence the returns of Ether in the first sub-sample as well as the volume of Ether in both sub-samples and the volume of Bitcoin in the first sub-sample.

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	Bitcoin	Ripple	Ether	Stellar	Litecoin
Return					
Mean	0.0009	0.0013	0.0030	0.0023	0.0002
St.Dev.	0.0395	0.0704	0.0778	0.0807	0.0590
Max	0.2251	1.0274	0.4123	0.7231	0.5103
Min	-0.2376	-0.6163	-1.3021	-0.3664	-0.5139
Skewness	-0.4194	2.3549	-3.3796	1.9354	0.5365
Kurtosis	8.5386	39.9188	67.5033	17.9068	15.8817
Log-Volume					
Mean	19.0892	15.4149	18.4436	13.2183	16.5895
St.Dev.	2.3170	3.2726	2.9631	3.7403	2.4052
Max	23.8947	22.9327	22.9441	21.1375	22.6637
Min	14.8656	9.0259	11.5340	6.1964	13.0851
Skewness	0.4715	0.5084	-0.4277	0.3023	0.4995
Kurtosis	1.7102	1.7612	1.9019	1.5612	1.6308
Stan-Idf					
Mean	0.0000	0.0000	0.0000	-0.0000	-0.0000
St.Dev.	1.0003	1.0003	1.0004	1.0003	1.0003
Max	3.6064	1.8696	3.1577	2.4826	3.1567
Min	-1.6420	-2.1239	-1.5358	-1.7908	-1.4135
Skewness	0.5268	-0.5980	0.7027	0.1916	0.6006
Kurtosis	3.2327	2.1621	3.0521	2.0923	2.7624

 Table 1 Summary statistics.

	Bitcoin	Ripple	Ether	Stellar	Litecoin
Panel A: Estimati	on results				
Return					
R_{t-1}	0.0001	0.0097	0.0432	0.0537**	-0.0075
R_{t-2}	-0.0368	0.0630***	0.0225	-0.0370	-0.0525**
R_{t-3}	0.0358	0.0368	-0.028	0.0343	0.0322
R_{t-4}	-0.0179	0.0151		-0.0278	
R_{t-5}	0.0134	0.0422*		0.0631**	
R_{t-6}	0.0531**	0.0463**		0.0208	
R_{t-7}				0.0007	
Vol_{t-1}	0.0031	0.0016	0.0091**	0.0059*	0.0013
Vol_{t-2}	-0.0014	0.0026	0.0017	-0.0009	-0.0003
Vol_{t-3}	0.0018	-0.0074**	-0.0115**	-0.0069*	-0.0011
Vol_{t-4}	0.0015	0.0001		0.0039	
Vol_{t-5}	-0.0009	-0.0013		-0.0004	
Vol_{t-6}	-0.0040	0.0038		-0.0058	
Vol_{t-7}				0.0039	
Idf_{t-1}	-0.0005	-0.0004	-0.0100*	-0.0020	-0.0012
Idf_{t-2}	-0.0032	0.0014	0.0027	-0.0031	0.0013
Idf_{t-3}	0.0034	-0.0040	0.0022	0.0075	-0.0038
Idf_{t-4}	0.0039	-0.0016		0.0021	
Idf_{t-5}	-0.0065**	-0.0056		-0.0077	
Idf_{t-6}	0.0026	0.0045		0.0005	
Idf_{t-7}				-0.0019	
Constant	-0.0002	0.0116	0.0165	0.0063	0.0014
Volume					
R_{t-1}	0.0707	0.6901***	0.6200***	1.7310***	0.3479*
R_{t-2}	0.5316**	0.3860**	0.0028	0.3783*	0.3145*
R_{t-3}	0.3146	0.4794**	-0.1705	0.1956	0.0634
R_{t-4}	0.1557	0.1552		0.1728	
R_{t-5}	0.2402	0.0322		0.2038	
R_{t-6}	0.0363	-0.3417*		-0.4946**	
R_{t-7}				-0.2911	
Vol_{t-1}	0.6190***	0.6910***	0.6273***	0.5567***	0.7524***
Vol_{t-2}	0.0200	-0.0008	0.1416***	0.1118***	0.0072
Vol_{t-3}	0.1071***	0.0487*	0.2244***	0.0978***	0.2262***
Vol_{t-4}	0.0785***	0.0518*		0.0250	
Vol_{t-5}	0.0036	0.0255		0.0845***	

Table 2Result	Its for the entire sample.

Vol _{t-6}	0.1666***	0.1669***		0.0237	
Vol_{t-7}				0.0906***	
Idf_{t-1}	0.0265	0.0592	0.1300***	0.1101***	-0.0201
Idf_{t-2}	-0.0572**	-0.1270***	-0.1243***	-0.1144**	-0.0022
Idf_{t-3}	0.0023	-0.0469	-0.0369	-0.0117	-0.0073
Idf_{t-4}	-0.0069	-0.0149		-0.0938*	
Idf_{t-5}	-0.0273	0.0785*		0.0616	
Idf_{t-6}	0.0484**	0.0004		-0.0101	
Idf_{t-7}				0.0333	
Constant	0.1064	0.2689***	0.1312*	0.1358**	0.2381***
Idf					
R_{t-1}	-0.0710	0.4580***	0.4076**	0.6870***	0.6147***
R_{t-2}	0.4207*	0.1514	0.3784**	0.3686***	0.0217
R_{t-3}	0.0625	0.1871*	0.2708*	0.0939	0.1170
R_{t-4}	0.4180*	0.0532		-0.0508	
R_{t-5}	-0.1841	-0.1515		0.1167	
R_{t-6}	0.2400	-0.0443		-0.1072	
R_{t-7}				-0.3242***	
Vol_{t-1}	0.0771***	0.0615***	0.0634**	-0.0259	0.0887***
Vol_{t-2}	-0.0536*	-0.0521***	-0.0554*	-0.0168	-0.0391
Vol_{t-3}	0.0341	-0.0191	-0.0048	0.0082	-0.0604**
Vol_{t-4}	-0.0536*	0.0082		-0.0140	
Vol_{t-5}	-0.0355	-0.0370**		0.0383**	
Vol_{t-6}	0.0257	0.0317**		0.0035	
Vol_{t-7}				0.0017	
Idf_{t-1}	0.7800***	0.5705***	0.7416***	0.6004***	0.4959***
Idf_{t-2}	-0.0948***	0.0454*	0.0312	-0.0409	0.2062***
Idf_{t-3}	0.0994***	0.0911***	0.1592***	0.0964***	0.2058***
Idf_{t-4}	0.0452	0.0423		0.0513*	
Idf_{t-5}	0.0326	0.0874***		-0.0343	
Idf_{t-6}	0.0875***	0.1285***		0.0911***	
Idf_{t-7}				0.1951***	
Constant	0.1111	0.1026**	-0.0665	0.0634	0.1805**
Panel B: Granger o	causality tests				
Ret does not Granger-Cause Stan-Idf	7.7669	24.958***	15.458***	43.406***	9.4696**
Log-Vol does not Granger-Cause Stan-Idf	14.968**	37.558***	5.8008	13.706*	19.593***
Stan-Idf does not Granger-Cause Ret Stan-Idf does not	7.7685	8.778	9.0327**	7.5071	6.8551*
Granger-Cause log- Vol	13.26**	23.647***	26.019***	19.058***	7.1143*

Ret does not Granger-Cause log- Vol	10.865*	27.854***	12.776***	76.928***	6.672*
Log-Vol does not Granger-Cause Ret	4.4503	7.7086	8.3529**	9.6139	0.2841

Note: *, ** and *** denote significance at the 10, 5% and 1% level, respectively.

	Bitcoin		Ether		
	Before break	After break	Before break	After break	
Panel A: Estima	tion results				
Return					
R_{t-1}	0.0040	-0.0446	0.0994**	0.0038	
R_{t-2}	-0.1001***	0.0679	-0.0035	0.0330	
R_{t-3}	0.0227	0.0524		0.0582	
Vol_{t-1}	0.0032	-0.0129	0.0100*	-0.0026	
Vol_{t-2}	-0.0037	0.0238	-0.0104*	0.0088	
Vol_{t-3}	0.0035	-0.0208		-0.0108	
Idf_{t-1}	-0.0011	0.0041	-0.0181**	0.0044	
Idf_{t-2}	-0.0021	-0.0072	0.0110	-0.0088	
Idf_{t-3}	0.0030	0.0045		0.0046	
Constant	-0.0519***	0.2190	0.0103	0.0986**	
olume					
R_{t-1}	0.0630	-0.0343	0.8365***	0.1904	
R_{t-2}	0.6825**	0.3302	-0.0708	0.0569	
R_{t-3}	0.4218	0.2187		0.1128	
Vol_{t-1}	0.6962***	0.6755***	0.6535***	0.6907***	
Vol_{t-2}	0.0619*	0.0687	0.2979***	0.0596	
Vol_{t-3}	0.2231***	0.1793***		0.2259***	
Idf_{t-1}	0.0125	0.0338	0.0928*	0.0998**	
Idf_{t-2}	-0.0870**	-0.0459	-0.1577***	-0.1298**	
Idf_{t-3}	0.0421	0.0125		0.0323	
Constant	0.3476***	1.7184***	0.7627***	0.4976**	
f					
R_{t-1}	0.5111*	-1.9620***	0.5812**	0.5024**	
R_{t-2}	0.5061*	0.0664	0.0655	0.4636**	
R_{t-3}	0.1678	0.4180		0.2880	
Vol_{t-1}	0.0685**	0.3322**	0.0636*	-0.0341	
Vol_{t-2}	-0.0543*	-0.4162**	-0.0733**	-0.0040	
Vol_{t-3}	-0.0255	0.0463		0.0586	
Idf_{t-1}	0.8096***	0.7306***	0.6267***	0.9560***	
Idf_{t-2}	-0.0639*	-0.0213	0.2593***	-0.2679***	
Idf_{t-3}	0.1836***	0.2262***		0.2486***	
Constant	0.2099*	0.8184	0.1431	-0.4236*	
Panel B: Grange	er causality tests				
et does not ranger-Cause	6.9176*	15.054***	4.8743*	13.607***	

Table 3 Results for the sub-samples.

Log-Vol does not Granger-Cause Stan-Idf	10.375**	7.9483**	4.3067	4.9688
Stan-Idf does not Granger-Cause Ret	1.5677	1.1404	8.0893**	0.7688
Stan-Idf does not Granger-Cause log- Vol	14.189***	2.2045	11.522***	7.3429*
Ret does not Granger-Cause log- Vol	8.2154**	3.1148	6.7432**	1.4092
Log-Vol does not Granger-Cause Ret	25.408***	4.7677	3.1364	6.1246

Note: *, ** and *** denote significance at the 10, 5% and 1% level, respectively.