Economics Letters 174 (2019) 39–41

Contents lists available at ScienceDirect

Economics Letters

journal homepage: www.elsevier.com/locate/ecolet

Price delay and market frictions in cryptocurrency markets☆

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HIGHLIGHTS

- We investigate the reaction time to unexpected relevant information of 75 cryptocurrencies.
- We measure reaction time using three price delay measures.
- The average price delay significantly decreases during the last three years.
- Price delay is highly correlated to market capitalization and liquidity.

ARTICLE INFO

Article history:
Received 27 September 2018
Received in revised form 17 October 2018
Accepted 19 October 2018
Available online xxxx

JEL classification:
G12
G14
G23

Keywords:
Cryptocurrency
Price delay
Market efficiency

ABSTRACT

We study the efficiency of cryptocurrencies by measuring the price's reaction time to unexpected relevant information. We find the average price delay to significantly decrease during the last three years. For the cross-section of 75 cryptocurrencies we find delays to be highly correlated with liquidity.

1. Introduction

The efficiency of cryptocurrencies and especially of Bitcoin has recently gained academic interest. In an efficient market as defined by Fama (1970) (EMH), prices should quickly incorporate new information without delay. Due to market frictions and lack of liquidity prices can react with a significant delay to new information making markets less efficient. The weak-form efficiency of Bitcoin is subject of many studies (Urquhart, 2016; Nadarajah and Chu, 2017; Vidal-Tomás and Ibañez, 2018; Kristoufek, 2018; Jiang et al., 2018; Bariviera, 2017; Tiwari et al., 2018; Khuntia and Pattanayak, 2018; Alvarez-Ramirez et al., 2018). Bitcoin is mainly found to be inefficient but to gain weak-form efficiency over time. For the cross-section of cryptocurrencies, the weak-form is investigated by Brauneis and Mestel (2018) showing liquidity and market cap to affect the efficiency. Wei (2018) studies the return predictability of 456 cryptocurrencies finding that there is a strong relationship with liquidity.

This study extends the efficiency debate of cryptocurrencies by investigating the average price delay of the market to new information. Using three delay measures as given in Hou and Moskowitz (2005) we show news to be faster incorporated in prices during the last three years. We further establish a connection between liquidity and price delay in the cross-section and find a strong relationship between estimated bid–ask spreads and price delay when not distinguishing between shorter and longer lags.

2. Data and delay measures

We obtain daily cryptocurrency prices, dollar volume, and market capitalization from coinmarketcap.com. Due to the dependence on other blockchains we do not include so-called "crypto tokens". Our sample covers the period from 31/08/2015, the starting month of Ethereum trading, to 31/08/2018. We use only cryptocurrencies with a complete time series and a market capitalization of at least USD 1 million at the end of August 2018 leaving a set consisting of 75 cryptocurrencies. Cf. Brauneis and Mestel (2018) for a similar setting. For the construction of our representative value-weighted market index we use all available cryptocurrencies in the sample period having available closing prices as well as market capitalization (867 cryptocurrencies).

☆ Declarations of interest: none.

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https://doi.org/10.1016/j.econlet.2018.10.025
0165-1765/

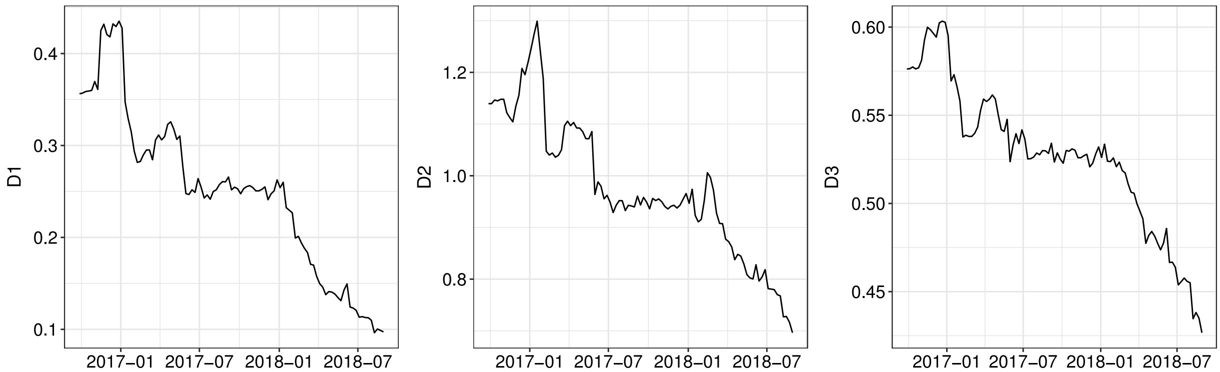

Fig. 1. Temporal evolvement of the three delay measures $\overline{D1}$, $\overline{D2}$ and $\overline{D3}$ (from left to right) using weekly returns in a rolling window of 52 weeks.

We use the three delay measures as proposed in Hou and Moskowitz (2005). The idea is to explain the individual returns by the market return and four weeks of lagged market returns:

$$r_{j,t} = \alpha_j + \beta_j R_{m,t} + \sum_{n=1}^{4} \delta_j^{(-n)} R_{m,t-n} + \epsilon_{j,t} \tag{1}$$

where $r_{j,t}$ is the log-return on cryptocurrency j and $R_{m,t}$ is the value-weighted market index log-return in week t. If the cryptocurrency responds immediately to news relevant for the cryptocurrency market, none of the $\delta_j^{(-n)}$ will differ from zero. The first delay measure $D1$ merely is one minus the ratio of the R^2 of the model in Eq. (1) with restricting $\delta_j^{(-n)} = 0, \forall n \in [1, 4]$ and the R^2 from regression (1):

$$D1 = 1 - \frac{R^2_{\delta_j^{(-n)}=0,\forall n\in[1,4]}}{R^2}. \tag{2}$$

Since longer lags are more severe for the efficiency of the market than shorter lags, we also use the delay measure:

$$D2 = \frac{\sum_{n=1}^{4} n\delta_j^{(-n)}}{\beta_j + \sum_{n=1}^{4} \delta_j^{(-n)}}. \tag{3}$$

Taking into account the precision of the estimates the final delay measure is given by:

$$D3 = \frac{\sum_{n=1}^{4} n\delta_j^{(-n)}/se\left(\delta_j^{(-n)}\right)}{\beta_j/se(\beta_j) + \sum_{n=1}^{4} \delta_j^{(-n)}/se\left(\delta_j^{(-n)}\right)} \tag{4}$$

where $se(\cdot)$ is the standard error. For the sample period, we calculate each delay measure for each of the 75 cryptocurrencies using weekly returns and a rolling window of 52 weeks. A week starts on Wednesday as in Hou and Moskowitz (2005). For the average price delay of the cryptocurrency market, we calculate the simple average for each delay measure of all cryptocurrencies which we denote by $\overline{D1}$, $\overline{D2}$ and $\overline{D3}$.

3. Results

The results for the average price delay using the three measures $\overline{D1}$, $\overline{D2}$ and $\overline{D3}$ are given in Fig. 1. The delay measure $\overline{D1}$ is between 0.35 and 0.45 at the beginning of our observation period and gradually declines to about 0.1. A value of one means that return variation is explained by lagged market returns only and a value of zero means that the lagged returns have no explanatory power for the variation of single cryptocurrency returns.

Thus, $\overline{D1}$ implies that cryptocurrencies significantly faster incorporated news related to the market over the last three years. The results of $\overline{D2}$ and $\overline{D3}$ confirm this finding by showing that longer lags become less prominent and the significance of the lagged market returns decrease.

To study the relation between price delay and liquidity in the cross-section we calculate $D1$, $D2$ and $D3$ over the whole sample period for each cryptocurrency. As explanatory variables we use the logarithm of market cap (logMC), the Amihud (2002) liquidity measure (ALM) defined as the ratio of absolute return and dollar volume, the Corwin and Schultz (2012) bid–ask spread estimator (CS) based on daily low and high prices and the turnover ratio (TR) defined as dollar volume divided by market cap. All explanatory variables are averaged over the sample period. Table 1 shows the correlation matrix and descriptive statistics. Due to the high correlation between CS and AML we do not include them together in regression specifications. However, we can anticipate that CS sufficiently captures the effects of both AML and TR.

Since $D1$, $D2$ and $D3$ are estimated values, we follow Brauneis and Mestel (2018) and Lewis and Linzer (2005) and run a feasible generalized least squares (GLS) regression. The latter find superior performance of feasible GLS over ordinary least squares when the explained variable is based on estimates. The results are given in Table 2.

While the bid–ask spread estimator CS is highly significant, ALM and TR seem not to possess explanatory power for the delay measure $D1$. Regarding the results from the feasible GLS of $D2$ and $D3$ we find both logMC and AML (only for $D3$) to gain more explanatory power. Only TR remains insignificant in all specifications. While the adjusted R-squared of the two $D1$ specifications differ greatly (0.45 and 0.26 respectively) the ones of the $D3$ specifications are almost equal (0.39 and 0.38 respectively). We hence conclude that both ALM and logMC gain explanatory power when differentiating between shorter and longer lags and incorporating their precision.

4. Concluding remarks

Adding to the recent literature of weak-form market efficiency we study the price delay in the cryptocurrency market. We use three delay measures and 75 cryptocurrencies to calculate the average price delay. Our findings show that price delay significantly decreases during the last three years giving further insights into the efficiency of the cryptocurrency market. Looking at the cross-section, we show that price delay is strongly related to liquidity and size. When not distinguishing between shorter and longer lags we find the Corwin and Schultz (2012) bid–ask spread estimator (together with market cap) to explain a large amount of the variations of price delay. Once we distinguish more between shorter and longer lags, a specification including market cap and the Amihud (2002) liquidity measure (and turnover ratio) performs similarly well in explaining price delay in the cross-section of cryptocurrencies.

Table 1
Correlation matrix on the left, descriptive statistics are given on the right side. ALM is multiplied by a thousand for readability.

	D1	D2	D3	logMC	CS	TR	ALM	Mean	Median	Min	Max	sd
D1	1							0.128	0.094	0.007	0.435	0.106
D2	0.87	1						0.931	0.925	0.338	1.683	0.341
D3	0.88	0.98	1					0.574	0.586	0.282	0.796	0.134
logMC	−0.40	−0.40	−0.41	1				16.75	16.35	11.33	24.78	2.422
CS	0.62	0.57	0.56	−0.42	1			0.059	0.045	0.009	0.285	0.050
TR	−0.04	−0.08	−0.05	0.15	−0.26	1		0.023	0.020	0.002	0.087	0.019
ALM	0.33	0.27	0.29	−0.24	0.78	−0.23	1	1.781	0.143	0.000	44.93	6.188

Table 2
Results from a feasible generalized least squares regression of $D1$, $D2$ and $D3$ on a set of explanatory variables.

Dependent variable	D1		D2		D3	
logMC	−0.114*	−0.279***	−0.674***	−1.072***	−0.323***	−0.472***
	(−1.96)	(−4.489)	(−2.709)	(−4.715)	(−3.337)	(−5.579)
CS	1.072***		2.418***		0.917***	
	(5.281)		(4.112)		(3.484)	
ALM		2.771		7.37		2.385**
		(1.493)		(1.045)		(2.127)
TR		0.048		0.602		0.578
		(0.093)		(0.4)		(0.972)
Intercept	0.371**	0.875***	2.616***	3.804***	1.393***	1.834***
	(2.209)	(5.077)	(3.801)	(6.119)	(5.246)	(8.061)
Adj.R^2	0.45	0.26	0.39	0.26	0.39	0.38
F-statistic	31.34***	9.68***	24.71***	9.84***	24.4***	16.4***

*Significance level: $p < 0.1$.
**Significance level: $p < 0.05$.
***Significance level: $p < 0.01$.

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