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Evidence for round number effects in cryptocurrencies prices

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ABSTRACT

This paper analyses the relationship between price clustering and trade volume in the Ether, Ripple and Litecoin cryptocurrencies. We examine at which digits price clustering exists and study the behaviour at different price levels and time frames. By using recent data to provide an updated view of price clustering in the cryptocurrency market, we find a remarkable level of price clustering at round prices: 5.29%, 2.84% and 2.97% for Ether, Ripple and Litecoin for every one minute at open prices, respectively. This paper reaffirms the negotiation hypothesis by finding that price clustering appears at prices at which traded volume is higher.

1. Introduction

The growth of cryptocurrencies, especially Bitcoin, has entailed a revolution as a payment method while establishing an alternative to the traditional financial markets due to speculation and the technological innovation behind them (blockchain). Since their inception, the most popular cryptocurrencies have been Bitcoin and Ether. However, in recent years, Ripple has strengthened its position in the top three and even briefly became the second most popular cryptocurrency by surpassing the market capitalization of Ether in September 2018. Another potential alternative and prominent rival to Bitcoin is Litecoin, which has positioned itself as a more practical and technologically superior alternative to Bitcoin.

The increasing interest in cryptocurrencies is reflected in the amount of academic research being conducted in this field. Most of the papers focus on Bitcoin, studying whether it is a real currency or comparing it to a safe haven like gold (Yermack, 2013; Popper, 2015; Cheah and Fry, 2015; Dwyer, 2015; Balcilar et al., 2017, amongst others). Other works have investigated its statistical properties to study whether it behaves like typical financial assets Bariviera et al. (2017). found a leptokurtic and negative skew behaviour as well as long-range memory at different time frames Katsiampa (2017). also suggested the importance of taking into consideration short and long-run components on Bitcoin's conditional variance. Nevertheless, it is remarkable that, as with Dyhrberg (2016), both found no asymmetric effect on volatility.

In this paper, we focus on another typical stylised fact in financial assets – price clustering. This phenomenon occurs when prices gather around specific values Brown et al. (2002). indicated that clustering may be the result of different factors such as human bias, uncertainty regarding the underlying value of an asset, or even cultural factors that influence the preference for certain numbers. Price clustering is well documented in the literature both across and within markets (Chung and Chiang, 2006) Aitken et al. (1996). investigated clustering in individual trades executed on the Australian Securities Exchange market, finding that traders have a

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Table 1
Descriptive statistics of Ether, Ripple and Litecoin open prices.

	Ether			Ripple			Litecoin		
	1 min	30 min	2 h	1 min	30 min	2 h	1 min	30 min	2 h
Mean	1522.086	1521.976	1522.035	0.4983	0.4983	0.499	176.3838	176.3796	176.4277
SD	437.4579	437.4887	437.9305	0.2966	0.2964	0.2976	38.8375	38.8262	38.9046
Max	2545	2533.3	2518.2	1.9645	1.9548	1.9119	296.84	295.21	295.1
Min	553	573.1	574.9	0.1719	0.1789	0.1789	95.12	99.32	100.9
Kurt	−0.3812	−0.3811	−0.379	7.822	7.8243	7.8133	−0.4435	−0.4424	−0.4210
Skew	−0.484	−0.4839	−0.4814	2.6429	2.6426	2.6447	0.3066	0.3069	0.3170
N	168,386	5613	1404	168,386	5613	1404	168,386	5613	1404

Table 2
Description of the indicators to test the first hypothesis.

Indicator	Formula	References	Description
Standard chi-squared test (W)	$W = \sum_{i=1}^{n} \frac{(O_i - E_i)^2}{E_i}$	Palao and Pardo (2012); Ikenberry and Weston (2008)	This statistic is calculated to test price clustering using the standard chi-squared test for the goodness of fit of the observed distribution to the expected distribution without clustering. O_i is the observed frequency of the last two digits and E_i is the expected frequency under uniform distribution. W is the distributed chi-squared with n-1 degrees of freedom. A high value of W means the existence of clustering is possible.
Herfindahl-Hirschman index (HHI)	$HHI = \sum_{i=1}^{n} f_i^2$	Grossman et al., (1997); Ikenberry and Weston (2007)	This indicator is a variation of the HHI that measures price concentration. The relative frequency of each possible combination of the last two digits is denoted as f_i. The value of the HHI under uniform distribution should be equal to $1/n$.
Standardized range (SR)	$SR = \frac{\max O_i - \min O_i}{E}$	Grossman et al. (1997)	The SR compares the extent of price clustering. E is the expected frequency of each combination of the last two digits when there is no price clustering. The SR is 0 when there is an absence of price clustering.
Regression model (F)	$F = \alpha + \beta D_i + \varepsilon$	Dowling et al. (2016)	This regression identifies the pair of digits in which price clustering appears. F is the absolute frequency of the pair of digits to the right of the decimal place. Each pair of digits is represented by a dummy variable, D_i, $i = 00,01,02\ldots$ to 99, which takes the value 1 for the decimals to which the test is done and 0 for the rest. To prove the existence of clustering, the result of the test should be the rejection of the null hypothesis, which implies a significant and positive β and, therefore, confirms the existence of clustering.

preference for prices ending in round and even numbers Gwilym et al. (1998). investigated clustering in financial derivatives and concluded that FTSE 250 futures and FTSE 100 options exhibit clustering at the decimals 0 and 5 for the final whole digit of prices. Regarding commodity markets, Bharati et al. (2012) studied the target pricing zone (TPZ) hypothesis for crude oil by examining price clustering and found clustering at 9 in the defined TPZ sub-periods Palao and Pardo (2012). tested price clustering in European carbon markets by using univariate and multivariate analysis, finding that prices cluster at 0 and 5 Brown and Yang (2016). used regression discontinuity and part difference-in-differences to prove that the price of assets tends to cluster at round numbers by studying betting exchange data on UK horse races.

The first study in the cryptocurrency market was the paper by Urquhart (2017) Hu et al. (2019). and Li et al. (2020) studied intra-day prices of Bitcoin and proved the existence of clustering at the intraday level. As an extension of these works, the goal of the present paper is to document evidence of price and volume clustering for the cryptocurrencies Ether, Ripple and Litecoin, considering intraday transaction data. Therefore, our two hypotheses are:

H1. Price clustering is present in the cryptocurrencies Ether, Ripple and Litecoin. This hypothesis says that the frequency distribution of the last two digits for the prices of the three cryptocurrencies does not follow a uniform distribution. We also examine at which digits price clustering exists and study its behaviour at different price levels and time frames.

H2. Volume clustering is present in the cryptocurrencies Ether, Ripple and Litecoin. This hypothesis tests whether prices at which clustering exists coincide with those where trading volume is higher.

The remainder of the paper is organised as follows. The following section describes the data source and the methodology used in the clustering analysis and the third section displays the results of the study for the three cryptocurrencies Section 4. concludes our discussion.

2. Data and methodology

We collected data from www.cryptodatadownload.com, which produces files for daily, hourly, and minute-by-minute time series pricing data for the spot (physical) market. The data consists of Ether, Ripple and Litecoin prices of Bitstamp in USD from 20 December 2020 to 16 April 2021 in the form of open, high and low prices. These cryptocurrencies are traded 24 h a day and 365 days a year so their close and open prices are almost the same. Therefore, following Xin et al. (2020), we ignored close prices. We considered various

Table 3
Most frequent last two digits of Ether, Ripple and Litecoin open prices and its frequencies (%).

	Ether			Ripple			Litecoin		
	1 min	30 min	2h	1 min	30 min	2h	1 min	30 min	2h
1st	00	00	00	00	00	00	00	00	00
(%)	5.29	5.83	5.48	2.84	3.01	2.85	2.97	2.98	3.06
2nd	50	40	88	01	01	41	50	50	50
(%)	1.24	1.34	1.71	1.42	1.51	1.57	1.67	1.89	2.14
3rd	99	50	75	50	47	63	80	27	27
(%)	1.08	1.3	1.64	1.36	1.25	1.5	1.13	1.43	1.78
4th	56	85	34	99	69	40	20	90	75
(%)	1.07	1.23	1.5	1.13	1.21	1.5	1.11	1.35	1.42
5th	01	79	3	52	50	66	60	60	56
(%)	1.04	1.23	1.5	1.11	1.21	1.42	1.11	1.34	1.35
χ^2	31629	1431	384.18	6615.7	334.21	143.86	7839.8	376.65	164.95
p-value	0.000	0.000	0.000	0.000	0.000	0.002	0.000	0.000	0.000
HHI	0.0119	0.0125	0.0127	0.0104	0.0106	0.011	0.0105	0.0107	0.0112
SR	4.409	5.256	5.057	1.944	2.352	2.493	2.09	2.298	2.635

The p-value is that $\chi^2$of a goodness-of-fit test with the null hypothesis of uniform distribution.

time frames: 1, 5, 15, and 30 min; 1 and 2 h[1] The tick size is 0.01 USD, so we considered two decimal places for all prices. When downloading Ripple data, we observed that its prices have more than two decimal places but, for the purpose of this study, we considered only the two last digits of the whole number. A descriptive analysis of the prices for the three cryptocurrencies is included in Table 1 and Table A1 of the Appendix.[2]

To test our first hypothesis and contrast the existence of price clustering we used four indicators (see Table 2): a chi-squared test, the Herfindahl-Hirschman index, the standardised range, and a regression model.

To test the second hypothesis, regarding the existence of volume clustering, we considered the variable *D,* which takes values from 00 to 99, and m as the total traded volume in USD for the cryptocurrency. The variable v_i represents the volume of USD traded in a certain moment at digits D. In this case, the subscript i takes values from 1 to n (the number of registers at digits D). The sum of all values of v_i is the absolute traded volume of USD at digits D. We divide the result by the total traded volume of USD for that cryptocurrency to obtain the relative volume (%):

$$V_D = \frac{\sum_{i=1}^{n} \ln v_i}{m} 100$$

The following section displays the results obtained to test our two hypotheses.

3. Results and discussion

3.1. Price clustering tests

First, we proved the existence of price clustering over various time frames for the prices of the three cryptocurrencies. The frequencies of the last two digits in USD of Ether, Ripple and Litecoin prices are presented in Table 3 and Table A2 of the Appendix. The frequency of the last two digits 00 is the highest for the three cryptocurrencies, being more than twice the expected frequency of 1%. The p-values of the χ^2goodness-of-fit test were lower than 0.05, which leads to the rejection of the null hypothesis of uniform distribution. Regarding the *HHI,* it was significantly different from 1/100 in all cases, which is the expected value in a uniform distribution. This also contributes to confirming the hypothesis of a frequency distribution that is different to uniform. Price clustering is also confirmed by the *SR* as its value was always much higher than 0. Therefore, the results of these three indicators contribute to verifying our first hypothesis and prove that price clustering is present in the cryptocurrencies Ether, Ripple and Litecoin.

To assess if there is any difference for clustering of open, high, and low prices, we set the time frame at every one minute. Observing Ether prices, we can see that 00 remains as the most frequent last two digits with frequencies approximately 2% higher than for Litecoin prices. For open, high, and low prices, 50 follows 00 as the most frequent price clustering.

In the case of Ripple, the most frequent last digits are 00 and 01. For open prices, the 00 frequency is almost three times higher than the expected frequency. For high prices, 00 becomes even more frequent with 01 less frequent. Finally, the cluster becomes stronger again for low prices, especially for 00.

[1] For reason of brevity, we only include results for 1 min, 30 min and 2 h. Results from other frequencies are available upon request.
[2] Tables in the main text of the paper show results for the open prices of the three cryptocurrencies. Results for high and low prices are presented in the Appendix.

Table 4
Results for the last two digits of Ether, Ripple and Litecoin open prices.

Ether						
	1 min		**30 min**		**2h**	
	D00		**D00**		**D00**	
β	7299.13		273.61		63.6	
p-value	0.00		0.00		0.00	
Adj-R^2	0.99		0.92		0.73	
Ripple						
	1 min		**30 min**		**2h**	
	D00	**D01**	**D00**	**D01**	**D00**	**D01**
β	3126.4	710.24	114.01	29.16	26.22	8.04
p-value	0.00	0.03	0.00	0.03	0.00	0.08
Adj-R^2	0.87	0.03	0.68	0.04	0.33	0.02
Litecoin						
	1 min		**30 min**		**2h**	
	D00	**D50**	**D00**	**D50**	**D00**	**D50**
β	3356.7	1134.5	111.9	50.37	29.25	16.12
p-value	0.00	0.001	0.00	0.00	0.00	0.00
Adj-R^2	0.84	0.09	0.58	0.1	0.35	0.1

β is the coefficient of the dummy variable of the regression. The p-value is that of the contrast which will be zero under the null hypothesis β, assuming a uniform distribution.

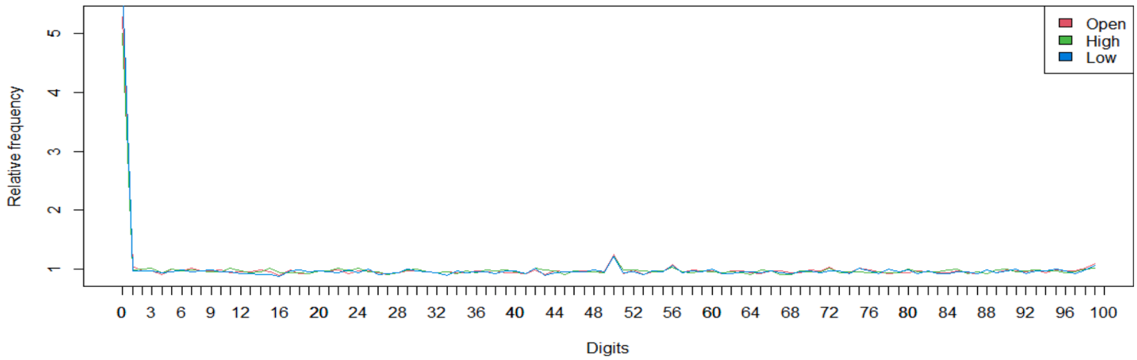

Fig. 1. Frequency distribution of the last two digits every 1 min for Ether.

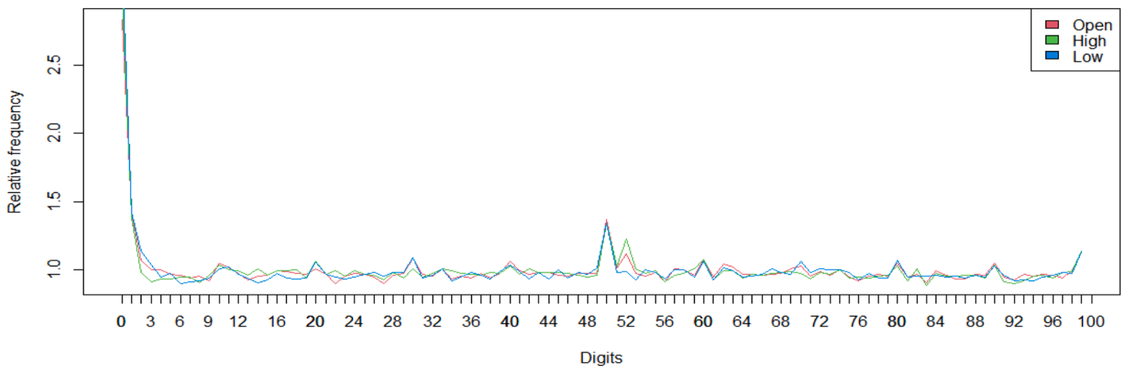

Fig. 2. Frequency distribution of the last two digits every 1 min for Ripple.

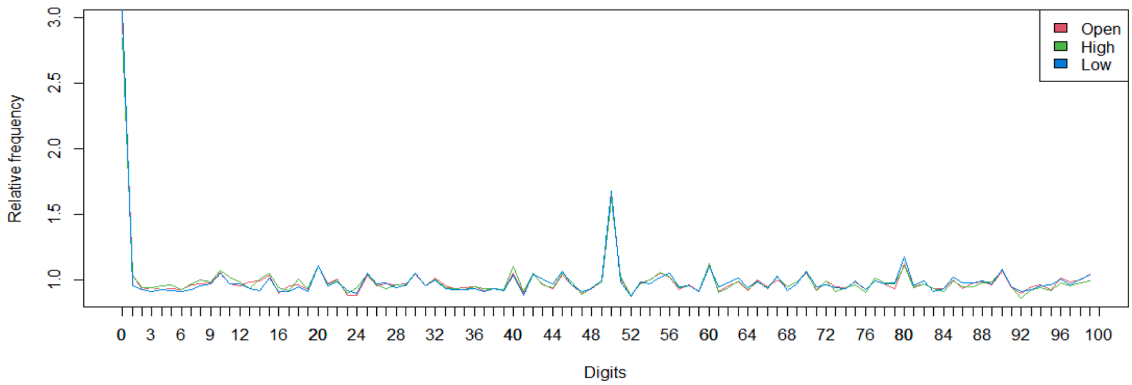

Fig. 3. Frequency distribution of the last two digits every 1 min for Litecoin.

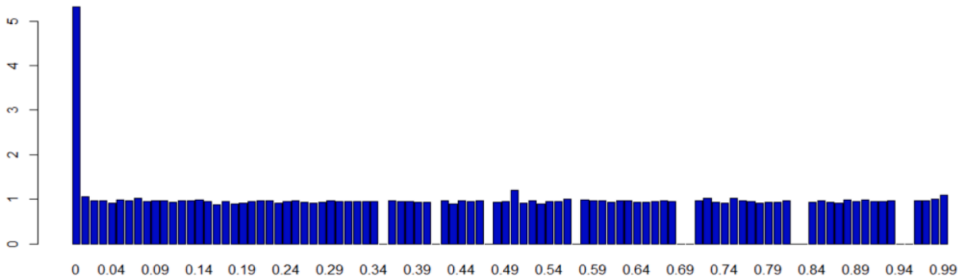

Fig. 4. Plot of the decimal values against the relative volume (%) every one minute for Ether open prices.

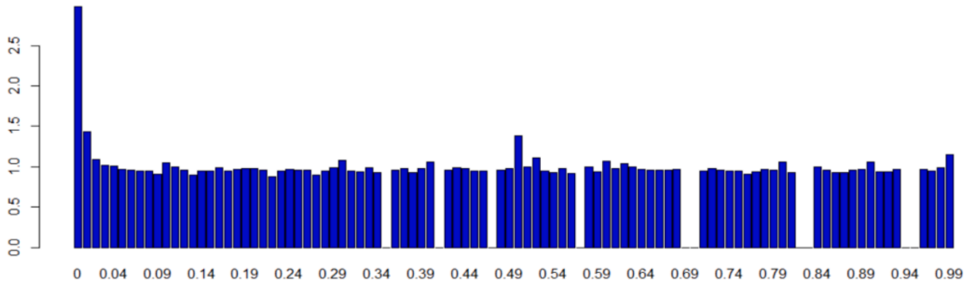

Fig. 5. Plot of the decimal values against the relative volume (%) every one minute for Ripple open prices.

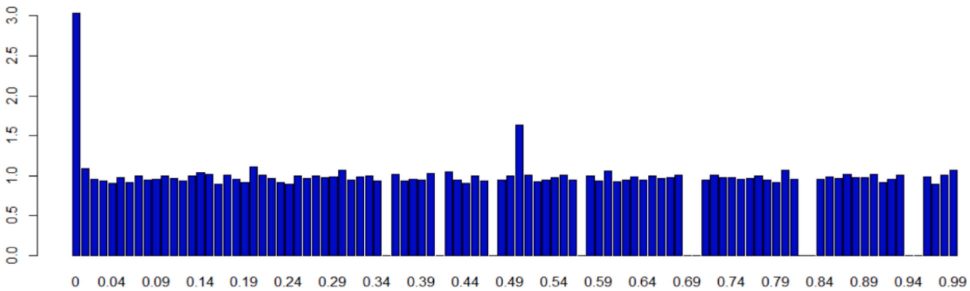

Fig. 6. Plot of the decimal values against the relative volume (%) for every one minute for Litecoin open prices.

Looking at Litecoin prices, we can observe that for open prices the last two digits frequency of 00 and 50 are significantly higher than 1%. In fact, the frequency of 00 is almost three times the expected frequency. The behaviours are similar for high prices; however, the frequency of both 00 and 50 decreases slightly compared to open prices, but they are still the most frequent. The clustering for 00 and 50 becomes stronger for low prices compared to open and high prices.

The results of the clustering test for Ether, Ripple and Litecoin are presented in Table 4 and Table A3 of the Appendix. We tested the existence of clustering for every pair of digits by calculating a regression for each dummy variable. Under the null hypothesis, β, the coefficient of the dummy variable, will be zero. However, if the null hypothesis is rejected with a low p-value, then β will be positive and significant, explaining the existence of clustering in the pair of digits represented by the tested dummy variable. We show the regression results for significant variables for each cryptocurrency.[3]

3.2. How timeframe affects price clustering

For the three cryptocurrencies, the longer the time frame, the stronger is the clustering. We can observe that in Table 3 and Table A1 of the Appendix, the values of both the *HHI* and the *SR* rise with an increase in the time frame. In addition, this time frame effect is stronger for high and low prices.

An explanation of this phenomenon is the psychological barrier hypothesis (Mitchell, 2001). When the time frame is short, there is more randomness in the price movement, which leads to a relatively high chance that high and low prices are not around prices ending in 00, and thus the cluster at 00 is lower. When the time frame gets longer, the effect of randomness disappears to some extent and clustering at round numbers becomes much more important for high and low prices. However, the 00 remains the most frequent last two digits in any case.

3.3. Clustering differences between the three cryptocurrencies

Even though clustering at round numbers occurs for the three cryptocurrencies, we can find some differences by examining the frequency distribution of the last two digits.

Ether only clusters at round numbers, being the frequency of the rest of the digits much less than 5%, which is the minimum frequency of 00 in this case. The most frequent last two digits after 00 are 01 for Ripple, which also significantly results in the regression model for all the time frames analysed. The same pattern as for Ripple is seen for Litecoin, but instead of clustering at 01, it clusters at 50 after round numbers. For Ripple, it can be noted that 50 is also significant in the regression model as the third most frequent last two digits, but only in the 1 min and 5 min time frames (see Figs. 1–3).

3.4. Volume clustering

In this section we test our second hypothesis – prices where trading volume is higher, coincide with prices where clustering exists Figs. 4–6. show the results of the volume test (V_D), representing the relative traded volume at each price every one minute.

In the case of Ether (Fig. 4), transactions with the highest volume also occur at round numbers at open, high, and low prices every one minute, covering 5.31% of the total traded volume. The rest of the prices cover less than 1.3% of the traded volume. As round number prices are significantly more frequent than any other digit, volume clustering only appears for round numbers.

Fig. 5 displays the relative trading volume of Ripple, which is higher at round prices, corresponding with 2.98% of the traded volume and 1.43% for prices with 01 decimals. These results seem consistent with price clustering results given that price clustering every one minute appears at round numbers and prices with 01 decimals.

Finally, for Litecoin, Fig. 6 shows that transactions at round prices are the ones with the highest volume (3.03% of the total traded volume) followed by transactions at prices with a 0.50 decimal (1.64%). These results coincide with price clustering results and confirm that, as for Litecoin, transactions with higher volume occur at prices where clustering exist.

The results of this section show that for each cryptocurrency, prices at which price clustering exist coincide with the ones at which traded volume is higher, confirming our second hypothesis.

4. Conclusions

The objective of this paper consisted of testing two hypotheses – H1: cryptocurrencies prices cluster, and H2: prices at which price clustering exist are the same at which trading volume in USD is higher.

After using four methodologies, we can confirm the existence of strong price clustering for the three cryptocurrencies considered. If we just consider the price levels of each cryptocurrency, the results of indicators *W, HHI* and *SR* show that low prices present a stronger clustering than open and high prices. The indicator *F* demonstrates that Litecoin clusters in 00 and 50, Ether in 00, and Litecoin in 00 and 01. This supports the conclusions of Urquhart (2017) about price clustering for Bitcoin, but in this case, we find the strongest price clustering at round numbers for Litecoin, Ether and Ripple. The effect of the timeframe results in a stronger clustering as the timeframe lengthens, which is explained by the psychological barrier hypothesis (Mitchell, 2001). Further research could extend this study to

[3] Clustering tests results for the rest of variables that do not present clustering are available in a R Studio file.

other cryptocurrencies to test, as expected, whether they exhibit similar behaviour.

As a contribution to the volume study, this paper is the first to examine the relationship between price clustering and traded volume for Litecoin, Ether and Ripple, to the best of the authors' knowledge. We found that the prices at which price clustering occurs are the same at which trading volume is higher, contributing to the negotiation hypothesis.

Compliance with ethical standards

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Declarations of interest

None.

CRediT authorship contribution statement

Raquel Quiroga-Garcia: Conceptualization, Methodology, Investigation, Writing – original draft, Writing – review & editing, Funding acquisition. **Natalia Pariente-Martinez:** Conceptualization, Methodology, Investigation, Writing – original draft, Software, Writing – review & editing. **Mar Arenas-Parra:** Software, Visualization, Investigation, Supervision, Writing – original draft, Writing – review & editing, Funding acquisition.

Appendix

See Tables A1, A2, A3

Table A1
Descriptive statistics of Ether, Ripple and Litecoin prices at high and low levels of different time frames.

Ether						
	1 min		**30 min**		**2 h**	
	High	**Low**	**High**	**Low**	**High**	**Low**
Mean	1523.11	1521.024	1530.541	1512.383	1539.188	1501.607
SD	437.461	437.4579	438.0571	436.6957	439.1598	435.6446
Max	2548.9	2543	2548.9	2533	2548.9	2494
Min	557.5	550	576.8	550	583.2	550
Kurt	−0.3768	−0.3859	−0.3552	−0.4091	−0.3306	−0.4338
Skew	−0.4855	−0.4822	−0.4964	−0.4716	−0.5075	−0.4566
N	168,386	168,386	5613	5613	1404	1404
Ripple						
	1 min		**30 min**		**2 h**	
	High	**Low**	**High**	**Low**	**High**	**Low**
Mean	0.499	0.4976	0.5035	0.4926	0.5093	0.4868
SD	0.2972	0.296	0.3004	0.2918	0.3049	0.2874
Max	1.9669	1.96	1.9669	1.9137	1.9669	1.9063
Min	0.1746	0.17	0.1870	0.1700	0.1992	0.1700
Kurt	7.8292	7.8126	7.855	7.8067	7.8793	7.8034
Skew	2.6451	2.6405	2.652	2.6335	2.6610	2.6271
N	168,386	168,386	5613	5613	1404	1404
Litecoin						
	1 min		**30 min**		**2 h**	
	High	**Low**	**High**	**Low**	**High**	**Low**
Mean	176.4652	176.2979	177.5818	175.0674	178.8975	173.5642
SD	38.8473	38.8276	39.0072	38.6442	39.2412	38.4601
Max	297.11	296.75	297.1	293.1	297.11	284.5
Min	95.99	94.44	99.6	100.0	99.68	100.0
Kurt	−0.4423	−0.4447	−0.4298	−0.4618	−0.4002	−0.4720
Skew	0.3073	0.3059	0.3108	0.2992	0.318	0.2976
N	168,386	168,386	5613	5613	1404	1404

Table A2
Most frequent last two digits of Ether prices and its frequencies (%).

Ether	1 min		30 min		2 h	
	High	Low	High	Low	High	Low
1st	00	00	00	00	00	00
(%)	5.00	5.82	7.89	8.44	11.25	10.61
2nd	50	50	52	50	99	19
(%)	1.22	1.21	1.26	1.32	1.64	1.57
3rd	56	99	23	31	23	29
(%)	1.03	1.05	1.26	1.26	1.57	1.5
4th	99	56	56	19	52	22
(%)	1.02	1.05	1.25	1.26	1.5	1.5
5th	42	42	22	94	65	53
(%)	1.01	1.01	1.19	1.23	1.42	1.42
χ^2	27,452	39,712	2807.5	3277.7	1584.4	1423.9
p-value	0.000	0.000	0.000	0.000	0.000	0.000
HHI	0.0116	0.0124	0.015	0.0158	0.0213	0.0201
SR	4.101	4.940	7.252	7.840	10.977	10.406
Ripple	**1 min**		**30 min**		**2 h**	
	High	**Low**	**High**	**Low**	**High**	**Low**
1st	00	00	00	00	00	00
(%)	3.04	3.24	4.97	5.15	7.26	6.91
2nd	01	01	01	01	01	01
(%)	1.38	1.42	2.28	2.3	3.13	2.78
3rd	50	50	52	50	52	50
(%)	1.34	1.34	1.96	1.67	1.78	1.99
4th	52	02	50	02	50	75
(%)	1.22	1.13	1.48	1.66	1.71	1.71
5th	99	99	99	30	98	59
(%)	1.13	1.13	1.44	1.43	1.64	1.42
χ^2	7884.8	9415.2	1194.8	1258.6	741.19	657.09
p-value	0.000	0.000	0.000	0.000	0.000	0.000
HHI	0.0105	0.0106	0.0121	0.0122	0.0153	0.0147
SR	2.155	2.345	4.401	4.562	6.985	6.629
Litecoin	**1 min**		**30 min**		**2 h**	
	High	**Low**	**High**	**Low**	**High**	**Low**
1st	00	00	00	00	00	00
(%)	2.84	3.06	4.1	4.45	5.84	6.84
2nd	50	50	50	50	50	50
(%)	1.62	1.68	1.94	2.08	2.42	2.35
3rd	60	80	70	20	11	23
(%)	1.13	1.18	1.41	1.3	1.5	1.71
4th	20	20	60	81	77	51
(%)	1.11	1.11	1.39	1.28	1.42	1.5
5th	80	60	80	70	65	43
(%)	1.11	1.11	1.35	1.26	1.42	1.5
χ2	6946.9	8542	733.01	841.03	441.55	599.49
p-value	0.000	0.000	0.000	0.000	0.000	0.000
HHI	0.0104	0.0105	0.0113	0.0115	0.0131	0.0143
SR	1.983	2.189	3.475	3.795	5.417	6.486

The *p-value* is that$\chi^2$of goodness-of-fit test with the null hypothesis of uniform distribution.

Table A3
The results for the last two digits of Ether, Ripple and Litecoin prices.

Ether	1 min				30 min				2 h			
	High		Low		High		Low		High		Low	
	D00	–	D00	–	D00	–	D00	–	D00	–	D00	–
β	6803.17	–	8191.05	–	390.79	–	422.10	–	145.42	–	136.33	–
p-value	0.00	–	0.00	–	0.00	–	0.00	–	0.00	–	0.00	–
Adj-R^2	0.99	–	0.99	–	0.96	–	0.96	–	0.94	–	0.92	–
Ripple												
	1 min				30 min				2 h			
	High		Low		High		Low		High		Low	
	D00	–	D00	–	D00	D01	D00	D01	D00	D01	D00	D01
β	3462.8	–	3807.2	–	225.13	72.61	235.23	73.61	88.85	30.27	83.80	25.22
p-value	0.00	–	0.00	–	0.00	0.00	0.00	0.01	0.00	0.01	0.00	0.01
Adj-R^2	0.89	–	0.9	–	0.75	0.07	0.77	0.07	0.75	0.08	0.75	0.06
Litecoin												
	1 min				30 min				2 h			
	High		Low		High		Low		High		Low	
	D00	D50	D00	D50	D00	D50	D00	D50	D00	D50	D00	D50
β	3137.5	1059.7	3512.3	1148.3	175.6	53.4	195.8	61.5	68.66	20.17	82.79	19.16
p-value	0.00	0.002	0.00	0.002	0.00	0.008	0.00	0.004	0.00	0.01	0.00	0.04
Adj-R^2	0.83	0.09	0.85	0.08	0.74	0.05	0.8	0.06	0.75	0.06	0.8	0.03

β is the coefficient of the dummy variable of the regression. p-value is that of the contrast in which under the null hypothesis β will be zero, assuming a uniform distribution.

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