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Price discovery of cryptocurrencies: Bitcoin and beyond

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HIGHLIGHTS

- We investigate efficiency / predictability of a large number of cryptocurrency returns time series.
- Also, using various measures, liquidity of cryptocurrencies is assessed.
- We find that efficiency is positively related to liquidity.

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ABSTRACT

Academic research on cryptocurrencies is almost exclusively directed towards Bitcoin. We extend existing literature by performing various tests on efficiency of several cryptocurrencies and additionally link efficiency to measures of liquidity. Cryptocurrencies become less predictable / inefficient as liquidity increases.

1. Introduction

Cryptocurrencies (CC hereafter), with Bitcoin leading the way, have boldly moved in the focus of attention in the last couple of months with media almost daily reporting on Bitcoin hitting a new all-time-high. Undoubtedly, CC evolved from a niche existence to a new asset class for which price time series are increasingly available by now and can be used for empirical analyses. One particularly interesting aspect is the question whether the highly volatile prices of CC evolve randomly over time or show some predictability. In this context, scientific work has almost exclusively focused on the price discovery of Bitcoin as the most prominent CC. Three recent papers in this journal (Urquhart, 2016; Nadarajah and Chu, 2017; Bariviera, 2017) examined the efficiency of Bitcoin's daily price returns. While Urquhart's and Bariviera's results point at inefficiency (i.e. violating Fama's weak form efficiency), Nadarajah and Chu's odd-power transformation of Bitcoin's price returns makes the data weak form efficient. However, efficient market hypothesis (EMH) seems inappropriate to explain CC prices. The reason is that EMH on the one hand assumes asset prices to always reflect and be driven solely by relevant information; on the other hand, investors are assumed to behave rational in the sense that they immediately incorporate all available information in an unbiased and coherent fashion. For reasons mentioned above, it is quite unclear what information is relevant for CC price discovery. Empirical tests of the EMH for CC markets is hence virtually impossible. Statistical analysis of empirical CC data is therefore restricted to test for predictability in prices in the sense of the random walk hypothesis, not to be confused with EMH. Besides predictability, CC prices can also be used to investigate market liquidity, which we aim to cover particularly in this paper. By now, we are not aware of any paper dealing with the relation of CC predictability and CC liquidity.

2. Data and methodology

CC data in this study covers the period from 08/31/2015 to 11/30/2017 and is provided by coinmarketcap.com, comprising

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Table 1
Descriptive properties of discrete daily returns (in % for mean, median, min, max, standard deviation) for the 10 biggest cryptocurrencies. p-values are reported for JB (Jarque–Bera test), KS (Kolmogorov–Smirnov) and ARCH (Engle's test for heteroscedasticity). MC denotes market capitalization in USD billions as of 11/30/2017.

CC	mean	median	min	max	sd	skew	kurt	JB	KS	ARCH	MC
Bitcoin	0.53	0.32	−18.74	23.94	3.55	0.13	8.96	0.00	0.00	0.00	165.54
Ethereum	0.95	−0.08	−27.06	35.36	7.14	0.87	6.77	0.00	0.00	0.00	41.41
Ripple	0.72	−0.35	−46.00	179.37	9.12	10.03	185.72	0.00	0.00	0.00	9.52
Dash	0.88	0.01	−21.59	54.92	6.22	2.03	15.50	0.00	0.00	0.00	5.26
Litecoin	0.57	0.00	−32.64	66.59	5.68	2.85	31.80	0.00	0.00	0.00	4.66
Monero	1.00	0.00	−25.41	79.43	7.84	2.66	21.91	0.00	0.00	0.00	2.63
Nem	1.36	0.00	−29.75	78.58	9.64	2.31	15.56	0.00	0.00	0.00	1.97
Stellar	0.82	−0.36	−30.67	106.07	10.08	4.56	41.82	0.00	0.00	0.00	1.16
Bitshares	0.79	−0.07	−32.41	68.20	8.75	2.40	17.19	0.00	0.00	0.00	0.36
Monacoin	0.85	−0.22	−23.28	134.48	9.47	5.81	66.04	0.00	0.00	0.00	0.30

Table 2
Results for the 10 biggest CC from tests assessing return predictability. Columns 2 to 7 report p-values of the Ljung–Box test (LB), the runs test, the variance ratio test (VR), the wild-bootstrapped [automatic] variance ratio test (wb [A]VR), the Bartels test and the Brock et al. BDS test. R/S refers to the rescaled hurst coefficient and MOE denotes Godfrey's measure of efficiency.

CC	LB	Runs	VR	wb VR	wb AVR	Bartels	BDS	R/S	MOE
Bitcoin	0.85	0.51	0.90	0.91	1.00	0.90	0.00	0.58	0.21
Ethereum	0.08	0.70	0.47	0.44	0.85	0.47	0.00	0.66	0.16
Ripple	0.00	0.81	0.67	0.92	0.96	0.67	0.00	0.67	0.12
Dash	0.11	0.70	0.33	0.21	0.69	0.33	0.00	0.54	0.19
Litecoin	0.00	0.01	0.98	0.46	1.00	0.98	0.00	0.53	0.15
Monero	0.00	0.25	0.83	0.59	1.00	0.83	0.01	0.62	0.16
Nem	0.03	0.28	0.75	0.25	0.99	0.75	0.00	0.68	0.17
Stellar	0.00	0.02	0.37	0.56	0.75	0.37	0.00	0.63	0.08
Bitshares	0.02	0.22	0.41	0.23	0.78	0.41	0.00	0.59	0.09
Monacoin	0.00	0.02	0.40	0.28	0.80	0.40	0.00	0.67	0.11

open, high, low and close prices, as well as dollar volume and market capitalization on a daily basis. Note that these data are volume weighted averages from a large number of different exchanges. We use only CC with a complete time series of all data and require a market capitalization of at least USD 1 million, leaving a total of 73 CC matching our criteria (the second largest CC, Ethereum, started in 08/2015, which is why we also start at this point in time). Descriptive statistics for discrete returns of the 10 CC showing the highest market capitalization are depicted in Table 1.

Extreme changes in CC prices are substantial; we observe maximum day-to-day losses exceeding 70%. The return series exhibit positive skewness for all CC, implying large positive price changes to be more likely than large negative changes. Finally, kurtosis is substantially higher than 3 for all CC, implying fat tailed distributions. We also performed tests for normality (Jarque–Bera, Kolmogorov–Smirnov), finding strong evidence against normality. Finally, Katsiampa (2017) reports time varying variance with Bitcoin's returns. Using Engle's ARCH test, we confirm heteroscedasticity for 68 CC in the dataset.

Concerning randomness of CC prices, Urquhart (2016) applies 5 different tests assessing the predictability of Bitcoin returns. We extend his choice of tests and derive results for our 73 currencies. Particularly, for each currency i's individual log-returns, $r_{i,t} = \ln(P_{i,t}/P_{i,t-1})$, we run (1) the Ljung and Box (1978) test with the null of no autocorrelation, (2) the runs test which tests for $\{r_i - \bar{r}\}$ coming in a random order (Wald and Wolfowitz, 1940), (3a) the variance ratio (VR) test (Lo and MacKinlay, 1988), assessing the null of: c times the variance of daily returns equals the variance of the sum of c daily returns), (3b) the Kim (2006) wild bootstrapped VR test based on Chow and Denning (1993), (3c) the Kim (2009) wild bootstrapped automatic VR test based on Choi (1999) (VR tests are run in their heteroscedastic robust version), (4) the Bartels (1982) test, and (5) the Brock et al. (1996) non-parametric BDS test. We also calculate (6) the Hurst exponent (cf. Urquhart (2017)) which may indicate persistence (long memory) in the returns time series.

Finally, we perform a non-parametric test for market efficiency (Godfrey, 2017), suggesting a measure of efficiency (MOE) ranging from zero (fully inefficient prices) to one (full efficiency). The basic idea lies in comparing the profits from 'active' trading to those from a buy-and-hold strategy. Assuming perfect foresight over a given investment horizon, active trading means taking long (short) positions in intervals of increasing (decreasing) prices, if profits thereof exceed accruing transaction cost. In other words, MOE measures how well a passive strategy performs relative to active trading which exploits every up- and downswing in a price time series taking transaction cost into account.

Liquidity of CC is assessed fourfold on a daily basis: first, the log-dollar volume, second, the turnover ratio (defined as dollar volume divided by market cap), third, the measure proposed by Amihud (2002), being the ratio of absolute return and dollar volume, and finally, the bid-ask estimate as proposed by Corwin and Schultz (2012) based on daily high and low prices.

3. Results

This section begins with results for our proposed tests of price predictability for the 73 CC under consideration. Referring to Table 2 entries in column LB denote p-values of the Ljung–Box test, at which the lowest p-value of lags 1 to 10 for each CC is reported. Similarly, for the different variance ratio tests (columns 4–6) we report the p-value from different test specifications, for (3a) we use $c = 2$, (3b) refers to $c = [2, 5, 10, 20, 40]$ and with (3c) c is set automatically as outlined in Andrews (1991). Columns Runs and Bartels show p-values for the runs test and the Bartels test, respectively. For the BDS test, we choose embedding dimensions from 2 to 5 and the distance ϵ is set such that for each CC 70% of return pairs lie within a distance of ϵ of each other (we use a Matlab script by Kanzler (1998)). Displayed results refer to the mean p-value of chosen embedding dimensions. R/S denotes the Hurst exponent from rescaled range statistic. Following Weron (2002), we calculate 95% confidence bounds for R/S of 0.665/0.335, indicating persistence/anti-persistence in returns time series. Finally, MOE is the measure of efficiency presented in Godfrey (2017). Transaction cost with MOE are set to 26 basispoints per trade which is taken from kraken.com, one of the biggest cryptoexchanges worldwide.

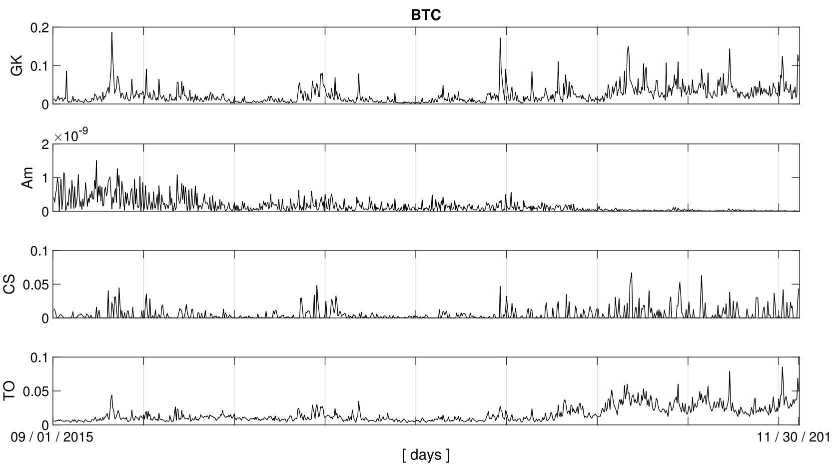

Fig. 1. Garman/Klass volatility (GK), Amihud's measure of illiquidity (Am), the Corwin/Schultz spread estimate (CS) and the turnover ratio (TO) for Bitcoin for the period of 09/01/2015 to 11/30/2017.

Table 3
Results from a feasible generalized least squares regression of $\overline{Rk}$ on a set of 4 explanatory variables in different specifications of the regression (left panel). Model validity is assessed by adjusted R^2 and the F-Test. Descriptives of regressors in the right panel of the table.

	(1)	(2)	(3)	(4)	mean	median	min	max	std
Am			115		3.8e−4	4.1e−5	1.6e−10	0.003	6.7e−4
CS	−289*	−330*	−244*	−244*	0.0409	0.0377	0.0048	0.1537	0.0269
logMC	2,15*		2,45*	2,43*	14.80	14.29	11.77	23.38	2.15
TO		202*	239*	249*	0.0230	0.0181	0.0017	0.0777	0.0176
adjR^2	.4678	.4203	.5272	.5338					
F	5.47*	4.94*	6.14*	6.23*					

* Denotes statistical significance at the 5% level.

Overall, we find Bitcoin to be the CC passing the most statistical tests of price randomness. This result for Bitcoin is in line with Nadarajah and Chu (2017), but contradicts previous results by Urquhart (2016) and Bariviera (2017) for an earlier timespan, finding Bitcoin prices to be inefficient. Another four CC in our dataset also pass all tests except BDS. Altogether, for the 73 CC under consideration, 15/12/0/11/14/16/5 CC pass exactly 1/2/3/4/5/6/7 out of the eight tests for randomness.

Results from these tests seem to reveal a pattern of increasing inefficiency (in terms of a higher number of failed tests) as CC become less capitalized. In order to further assess this conjecture, for each efficiency test (LB to BDS), we first rank CC by their respective p-value. Since all tests state the null of no predictability, a higher p-value indicates increased consistency with efficiency. For the Hurst-coefficient, we rank CC by their absolute deviation from 0.5 and for MOE CC are ranked by their MOE-number. The mean rank for CC i, referred to as $\overline{Rk}_i$, of all 9 tests of efficiency depicted in Table 2 serves as our ultimate measure of efficiency (this number ranges from 8.5 [Mintcoin] to 67.11 [Bitcoin]). Next, we want to examine drivers of $\overline{Rk}_i$ and identify measures of liquidity of individual CC, the market capitalization and volatility as suited candidates. Fig. 1 exemplarily plots Bitcoin's daily volatility (measured by the OHLC estimator proposed by Garman and Klass (1980)) as well as three measures of liquidity, namely Amihud, Corwin–Schultz and the turnover ratio.

Now, for all 73 CC, we first calculate the daily time series of Garman/Klass volatility, Amihud's illiquidity measure, the Corwin/Schultz spread estimator, turnover ratio, log-dollar volume and log-market capitalization. The time series mean results in the CC-specific variables $\overline{GK}_i$, $\overline{Am}_i$, $\overline{CS}_i$, $\overline{TO}_i$, $\overline{logV}_i$ and $\overline{logMC}_i$, which serve as explanatory variables in a regression. Following Lewis and Linzer (2005) who find superior performance of feasible generalized least squares regression (FGLS) over ordinary least squares (OLS) when the explained variable is based on estimates (recall that $\overline{Rk}_i$ builds on several estimates of market efficiency) we opt for this regression specification.

Yet, we skip $\overline{logV}_i$ which is highly correlated to $\overline{logMC}_i$ and features the highest variance inflation factor. The same applies to $\overline{GK}_i$, which leaves 4 explanatory variables. Univariate regressions of $\overline{Rk}_i$ on only one of these explanatory variables reveal statistically highly significant coefficients. Table 3 reports results for four different multivariate specifications (Models (1) to (4)) as well as descriptive properties of regressors.

Overall, we find model (4) to be most appropriate, implying that 'efficiency' of cryptocurrency returns is driven by liquidity (illiquidity) and size. The Amihud measure in model (3) does not show statistical significance, liquidity aspects of efficiency therefore seem to be sufficiently captured by CS and TO.

4. Conclusion

Urquhart concluded his 2016 paper by stating that Bitcoin is not weakly efficient, but tends to become efficient in the second half subsample. On the one hand, we find Bitcoin the least predictable (i.e. most 'efficient') CC and corroborate Urquhart's conjecture. For 73 CC, we find a heterogeneous pattern of efficiency, probably related to liquidity and size. In the attempt to further understand the underlying drivers of efficiency, we extend existing literature by identifying the turnover ratio as a measure of liquidity to positively affect efficiency, the Corwin–Schultz estimate of the bid–ask spread shows the expected negative effect towards efficiency, and market capitalization which proxies for size relates positively to efficiency.

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