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Does Bitcoin dominate the price discovery of the Cryptocurrencies market? A time-varying information share analysis

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ABSTRACT

Using a time-varying vector error correction model (VECM), we examine the dynamic information shares of the top four Cryptocurrencies: Bitcoin (BTC), Ethereum (ETH), Ripple (XRP) and Litecoin (LTC) over 1/1/2016–31/12/2019. Although steadily decreasing, the information share of BTC is still the largest as of end-2019. The individual dominances of market capitalization and trading volume can explain 20% of variations of the BTC information share but only 6% of those for ETH.

1. Introduction

The global Cryptocurrencies (CC) market has been growing fast over the past few years, with the rapid development of the blockchain technology. As shown in Fig. 1(a), the total market capitalization increases from US$7 billion at start-2016 to over US$790 billion at start-2018. Although shrunk over 80% by end-2018, the total market capitalization increases fast again in 2019 and ends up with nearly US$200 billion at end-2019. Excluding those forked from Bitcoin (e.g. Bitcoin Cash), we plot logged daily close price (in US$) of the top four CC (based on the total market capitalizations as of end-2019), Bitcoin (BTC), Ethereum (ETH), Ripple (XRP) and Litecoin (LTC), in Fig. 1(b) over 1/1/2016–31/12/2019. Different from traditional currencies, prices of the top four CC always move together and show very similar patterns. Consistent with this, we observe in Table 1 that Pearson correlations of the prices of four CC are very close to 1. Even the corresponding daily returns of those CC still exhibit considerably large correlations. As found in [2], major CC demonstrate homogeneous volatility behaviours. Given those facts and their high-degree technical relevance in blockchain, it is reasonable to assume that major CC are simultaneously influenced by shocks on the CC market. Therefore, it is important to understand how each CC can contribute to the market-level price discovery process.

Existing analyses of CC mostly focus on Bitcoin only [4,14], which dominates at around 63% of the total CC market capitalization at end-2019, or extend to efficiency and/or liquidity of other CC [3,9]. Little has been done to compare contributions of major pairs to the price discovery of the CC market as a whole. For instance, studies [6,7,12] have investigated the price discovery and spillovers of BTC traded on different exchanges. A recent research [5] further examines the interconnectedness across BTC and some usual risk heaven pairs (e.g. gold). Those works, however, do not consider other CC pairs. On the other hand, a related recent study of [1] examines the extreme behaviour, namely the co-explosivity, of the top five capitalized CC. It is argued that ETH is the most influential pair, and its impacts rapidly increase during bubble periods. The authors also found that the impact of BTC on other CC is not homogeneous over time. Consistent with this, as shown in Fig. 2, dominances of the top four CC have largely changed through time. Thus, it is of interest to examine if a general (not necessarily extreme) market-level price discovery process is time-dependent. However, standard existing methodologies are only applicable to the static, or time-independent, cases.

To resolve the methodological incompetency, this paper firstly proposes a time-varying vector error correction model (VECM), extending from the seminal work of [8]. Based on the new model, we further derive two time-varying information share measures, extended from two popular static measures proposed in [10] and [13]. Hence, we contribute to the methodological innovation that enables the investigation of the dynamic price discovery. As for the empirical examination, this paper is the first to consider the information shares of the CC market as a whole on a time-varying basis.

Comparing to the recent study by Giudici and Pagnottoni [6], which also employs the VECM, there are two major methodological differences. First, we focus on the information share (IS) by

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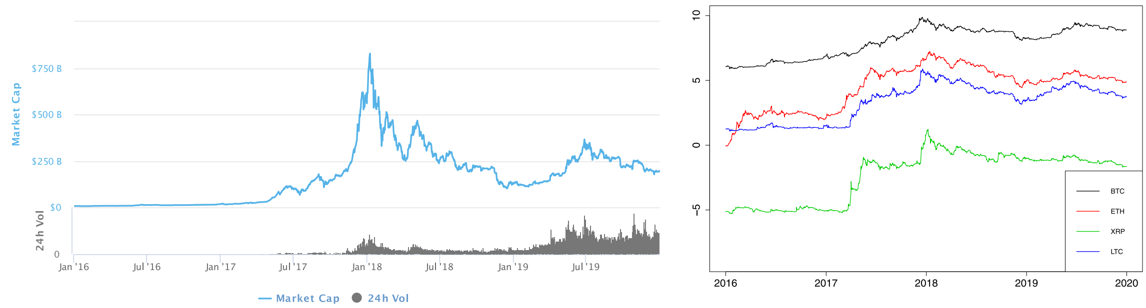
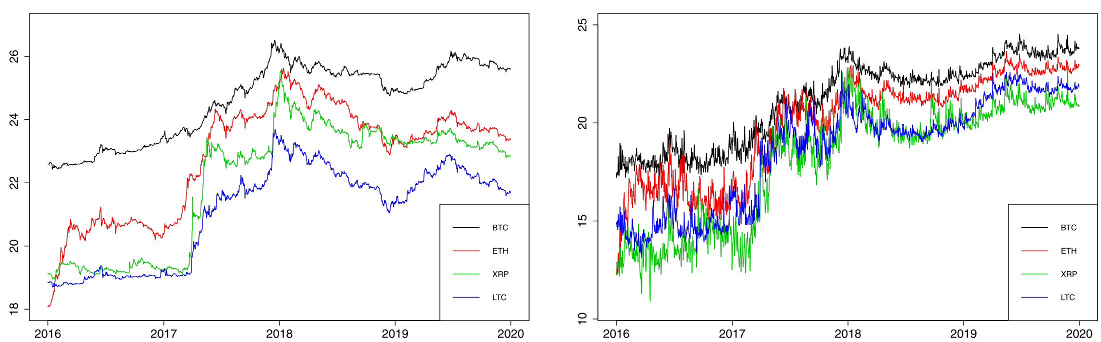
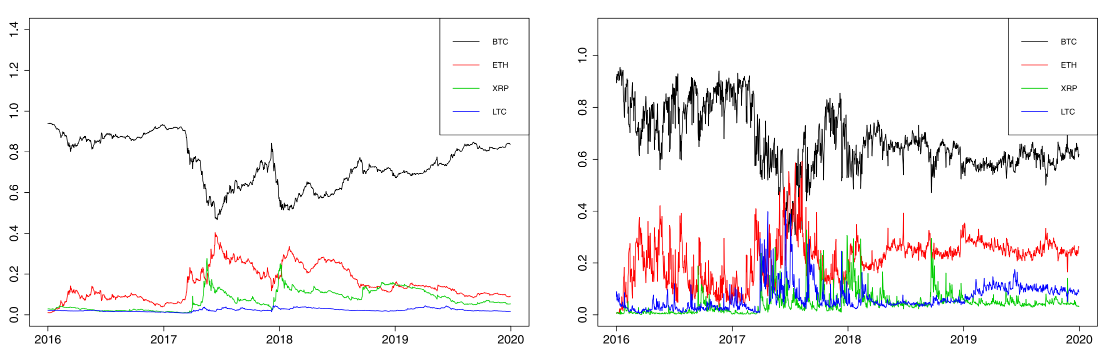


(a) Total Market Capitalizations and Trading Volumes (b) Prices of Selected Cryptocurrencies

Fig. 1. Daily market capitalizations, trading volumes and logged prices of CC: 1/1/2016–31/12/2019.



(a) Logged Market Capitalizations (b) Logged Trading Volumes



(c) Market Capitalizations (% out of the four CC) (d) Trading Volumes (% out of the four CC)

Fig. 2. Daily market capitalizations and trading volumes of selected CC: 1/1/2016–31/12/2019.

Table 1
Correlations of logged daily prices and returns of selected CC: 1/1/2016–31/12/2019.

CC	Logged prices				Returns			
	BTC	ETH	XRP	LTC	BTC	ETH	XRP	LTC
BTC	1.0000	0.9299	0.9397	0.9651	1.0000	0.4908	0.3453	0.6277
ETH		1.0000	0.9505	0.9595		1.0000	0.3367	0.4778
XRP			1.0000	0.9731			1.0000	0.4004
LTC				1.0000				1.0000

considering in-sample residuals, whereas [6] focuses on the out-of-sample forecast error variance decompositions to construct the metric of Total Spillover Index (TSI). IS measures that when a common shock arrives on the market, the relative efficiency that the shock is reflected by the prices of each instrument. In contrast, TSI measures the spillover effect. That is, the relative variations of one instrument due to the shock of another instrument. Second, the dynamic modelling specification is different. Our approach is the local constant time-varying coefficients estimated using a non-box kernel, such that different weights are assigned to all observations. The dynamic specification of [6] is a running-window with fixed length. This is equivalent to a box kernel with equal weights assigned to included observations. In addition, there are two empirical differences. First, our paper discusses the price discovery of the CC market using the top four capitalized pairs, while [6] focuses on BTC only, and the prices are quoted from various exchanges. Second, implications of findings are different. Our results suggest declining leading roles of the BTC in the dynamic price discovery process. In the work of [6], the authors identify Bitfinex and Coinbase as leading exchanges of BTC with evidenced time-varying connectedness across exchanges.

2. Data and methodology

CC data studied in this paper are sourced from coinmarketcap.com and cover the period 1/1/2016–31/12/2019, including daily close price, market capitalization and dollar trading volume. As plotted in Fig. 2, both logged market capitalizations and trading volumes of the four CC enjoy similar increasing patterns from 2016 to early-2018. After a two-year recession period, they then demonstrate inversed V-shape market capitalizations in 2019, whereas their trading volumes increase more steadily. Those observations are consistent with the trends of the entire CC market, as shown in Fig. 1(a). To study the potential dynamic information share of the selected four CC, we propose the following time-varying VECM, based on the seminal work of [8].

$$\triangle \boldsymbol{Y}_t = \boldsymbol{\alpha}_t \boldsymbol{\beta}^T \boldsymbol{Y}_{t-1} + \sum_{i=1}^{k} \boldsymbol{A}_{i,t} \triangle \boldsymbol{Y}_{t-i} + \boldsymbol{\varepsilon}_t \tag{1}$$

where $\boldsymbol{Y}_t$ is the logged daily close prices. Each column of $\boldsymbol{\alpha}_t$ therefore consists of the corresponding coefficients at time t and measures the time-varying influences of each row of the co-integration matrix $\boldsymbol{\beta}^T \boldsymbol{Y}_{t-1}$. $\boldsymbol{A}_{i,t}$ are time-varying autoregressive coefficients.

Following the information share (IS) approach of [10], (1) can be rewritten to

$$\boldsymbol{Y}_t = \boldsymbol{Y}_0 + \boldsymbol{\Psi}_t(1) \sum_{i=1}^{t} \boldsymbol{\varepsilon}_i + \boldsymbol{\Psi}_t^M(L) \boldsymbol{\varepsilon}_t. \tag{2}$$

We therefore measure the IS of the jth CC at time t as

$$IS_{j,t} = \frac{([\boldsymbol{\psi}_t \boldsymbol{F}_t]_j)^2}{\boldsymbol{\psi}_t \boldsymbol{\Omega}_t \boldsymbol{\psi}_t^T} \tag{3}$$

where $\boldsymbol{\Omega}_t$ is the variance matrix of $\boldsymbol{\varepsilon}_t$ at time t. $\boldsymbol{F}_t$ is its corresponding Cholesky fractionation. $\boldsymbol{\psi}_t$ is the identical row of the 4×4 matrix $\boldsymbol{\Psi}_t(1)$ in (2), which satisfies that

$$\boldsymbol{\beta}^T \boldsymbol{\Psi}_t(1) = \boldsymbol{0} \text{ and } \boldsymbol{\Psi}_t(1)\boldsymbol{\alpha}_t = \boldsymbol{0}.$$

$IS_{j,t}$ measures the percentage contribution of the jth CC to the price discovery, and all the four IS sum up to 1 at each t. The time-varying parameters are estimated using a local constant method with the Epanechnikov kernel, for which the bandwidth is chosen using the leave-one-out method. The estimation details can be found in [11].

However, since $\boldsymbol{F}_t$ depends on the orders of CC in $\boldsymbol{Y}_t$, the IS measure is not unique. We then collect all estimates of the 24 permutations of the four CC and use the arithmetic average as the IS measure of each CC. The reason is that it is argued that the popular approach of using the midpoint of high and low IS measures will not necessarily sum to 1 [13]. Apart from IS, Lien and Shrestha [13] develop a modified information share (MIS), which is invariant against the order of vectors in $\boldsymbol{Y}_t$. To check the robustness of our results, we also consider a time-varying MIS (MIS_t), which is constructed as in (3), except that $\boldsymbol{F}_t$ is replaced by

$$\boldsymbol{F}_t^M = [\boldsymbol{G}_t \boldsymbol{\Lambda}_t^{-1/2} \boldsymbol{G}_t^T \boldsymbol{V}_t^{-1}]^{-1}$$

where $\boldsymbol{\Lambda}_t$ is a diagonal matrix with diagonal elements being the eigenvalues of the correlation matrix corresponding to $\boldsymbol{\Omega}_t$. $\boldsymbol{G}_t$ consists of the corresponding eigenvectors as its columns. $\boldsymbol{V}_t$ is a diagonal matrix containing the time-varying standard deviations of $\boldsymbol{\varepsilon}_t$ on the diagonal. It can be verified that $\boldsymbol{F}_t^M$ defined in this way also factorizes the covariance matrix of residuals, such that $\boldsymbol{\Omega}_t = \boldsymbol{F}_t^M (\boldsymbol{F}_t^M)^T$.

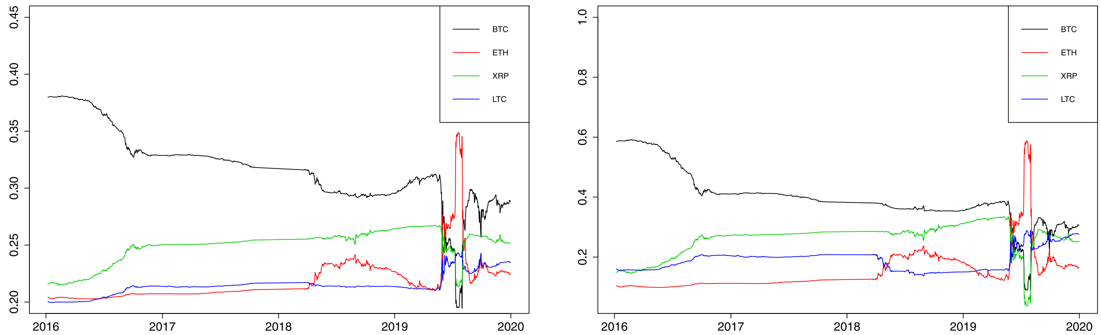
3. Empirical results

Both the Augmented Dickey–Fuller (ADF) and Phillips–Perron (PP) unit-root tests suggest that logged daily close prices of all BTC, ETH, XRP and LTC are I(1), whereas the Johansen co-integration test supports three co-integrations that exist among them. As assumed in [10], we set the three columns of $\boldsymbol{\beta}$ to $(1, 0, 0 - 1)$, $(0, 1, 0, -1)$ and $(0, 0, 1, -1)$ as in (1), with the logged prices of ETH ordered last (i.e. being subtracted from other series). The three resulting sequences passed both ADF and PP tests to be I(0). All test results are available upon request. Therefore, using a time-varying VECM with five lags as specified in (1), we fit the logged daily close prices of the four CC. The resulting time-varying IS and MIS are plotted in Fig. 3(a) and (b), respectively. Overall, the fitted IS_t of BTC steadily decreases from 0.38 at start-2016 to 0.29 at end-2019, except for a sudden drop to 0.20 in mid-2019 followed by a quick recovery back to 0.30. As for the other three CC, in general, they increase slowly over 2016–2019. The fluctuation in mid-2019 has negatively impacted XRP but positively affected ETH and LTC. Throughout the entire investigation period, BTC dominates in almost all times except for mid-2019. IS of XRP is distinctively higher than that of LTC. Although ETH has the second largest market capitalization and trading volumes, its IS is the smallest one in more than half of the studied period. Despite the measurement differences, the shapes of MIS_t of all CC are consistent with those of the IS_t. The only difference is that MIS of BTC, XRP and LTC are close to each other and are well above that of ETH at end-2019. The descriptive statistics of IS_t and MIS_t, including the mean, standard deviation (Std. Dev.), 5% quantile ($Q_{0.05}$) and 95% quantile ($Q_{0.95}$), are presented in Table 2.

Noticing that IS_t and MIS_t of each CC demonstrate similar patterns as those shown in Fig. 2(c) and (d), we now explore the impacts of the market capitalizations, or Mar. Cap., and trading volumes, or Vol., (both measured in percentages out of the four CC) on the dynamic information share measures. We consider three models: (1) Mar. Cap. only; (2) Vol. only; and (3) Mar. Cap. and Vol. A linear regression with Newey–West standard errors is then fitted for IS_t and MIS_t of each CC separately. As shown in Table 3, Mar. Cap. is only individually significant in Models 1 and 3 for XRP, whereas Vol. is individually significant in Models 2 and 3 for BTC, ETH and LTC. All significant estimates are positive, which is consistent with the similar time-varying patterns observed in Figs. 2 and 3. As for the explained variations of the dynamic information share measures, considering both Mar. Cap. and Vol. leads to an R^2 of around 21%, 6%, 32% and 14% for IS_t of BTC, ETH, XRP and LTC, respectively. Results of MIS_t are only marginally different from those of IS_t described above.

4. Concluding remarks

Extending the price discovery and spillover of the BTC across various exchanges as considered in [5] and [6], we analyse the dynamic information shares of the top four CC pairs. Although experiencing a declining importance over time, BTC is still the most dominant CC in the process of the market-level price discovery. BTC's trading volume is positively associated with this time-varying information share and explains its 20% variations. As the second mostly capitalized and traded CC, ETH contributes least to the price discovery, with only 5% information share explained by its trading volume. This is different from the findings of [1], which



(a) IS (b) MIS

Fig. 3. Estimated IS and MIS of selected CC: 1/1/2016–31/12/2019.

Table 2
Summary of estimated IS and MIS of selected CC: 1/1/2016–31/12/2019.

	IS				MIS			
CC	Mean	Std. Dev.	$Q_{0.05}$	$Q_{0.95}$	Mean	Std. Dev.	$Q_{0.05}$	$Q_{0.95}$
BTC	0.3967	0.0887	0.2744	0.5866	0.3171	0.0329	0.2716	0.3798
ETH	0.1513	0.0697	0.0998	0.2371	0.2185	0.0205	0.2030	0.2424
XRP	0.2611	0.0525	0.1540	0.3273	0.2494	0.0141	0.2168	0.2663
LTC	0.1909	0.0356	0.1478	0.2659	0.2150	0.0090	0.2000	0.2347

Table 3
Regression analysis of IS and MIS against dominances of market capitalization and dominances of trading volumes: 1/1/2016–31/12/2019.

CC	Models	IS			MIS		
		Mar. Cap.	Vol.	R^2	Mar. Cap.	Vol.	R^2
BTC	1	0.0840		0.0915	0.2268		0.0916
		(0.0848)			(0.2351)		
	2		0.1266***	0.2079		0.3352***	0.2001
			(0.0273)			(0.0768)	
	3	−0.0044	0.1296***	0.2080	−0.0032	0.3374***	0.2002
		(0.0481)	(0.0393)		(0.1359)	(0.1030)	
ETH	1	0.0013		0.0000	0.0082		0.0001
		(0.0652)			(0.2286)		
	2		0.0511***	0.0446		0.1763***	0.0460
			(0.0217)			(0.0756)	
	3	−0.0326	0.0656*	0.0566	−0.1078	0.2243*	0.0574
		(0.0512)	(0.0352)		(0.1717)	(0.1192)	
XRP	1	0.1663***		0.3211	0.5545***		0.2562
		(0.0702)			(0.2360)		
	2		0.1256***	0.1458		0.4132***	0.1132
			(0.0333)			(0.1120)	
	3	0.1582***	0.0145	0.3223	0.5328***	0.0389	0.2568
		(0.0515)	(0.0239)		(0.1981)	(0.0674)	
LTC	1	0.1589		0.0178	−0.3044		0.0042
		(0.9019)			(8.2007)		
	2		0.0708***	0.1429		0.2147***	0.0849
			(0.0232)			(0.0648)	
	3	−0.0400	0.0734***	0.1438	−1.0824	0.2871***	0.1284
		(0.1367)	(0.0269)		(0.6908)	(0.0813)	

Note: Numbers in the parentheses are the corresponding Newey–West standard errors. *, **, *** indicate significance at 10%, 5% and 1%, respectively.

supports ETH's centrality role in the co-explosivity of major CC pairs during bubble periods. Nevertheless, it is worth noting that IS of ETH overtakes that of LTC after the bubble-burst event at around early-2018, which is partially consistent with [1]. Despite this, ETH's relative secondary role in the general (non-extreme) price discovery process may be caused by its unique functions (e.g., creating and distributing tokens) which are different from pure financial assets like BTC and LTC [1], making it less sensitive to the usual CC market shocks. Future research should investigate which and how special features of ETH contribute to this insensitivity.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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