Convergence in Cryptocurrency Prices?
The Role of Market Microstructure

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Revised and Resubmitted
June 2020

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Abstract

Do we observe convergence between cryptocurrencies over time? This study explores this question with eight major cryptocurrencies in circulation and posits a framework to evaluate whether shifts in their market microstructures drive convergence. Three main findings emerge. First, convergence can emerge between cryptocurrencies with distinct technological functions and classifications. Second, market microstructure behavior drives convergence. Third, estimated transition paths show tighter convergence for half of our sampled cryptocurrencies during the time when the Chicago Board of Exchange (CBOE) introduced bitcoin futures contracts.

Keywords: Bitcoin; club convergence; cryptocurrencies; market microstructure
JEL classification: C58; G14; G17

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1. Introduction

With the emergence of cryptocurrencies, certain studies have investigated the market efficiency of the cryptocurrency market (Tran and Leirvik 2019; 2020, Hu et al. 2019, and citations therein). As proposed by Fama (1970; 1991), the strong form of the efficient market hypothesis (EMH) implies that all available information is reflected in the price of a security. As an alternative to the static view of the EMH, Lo (2004) argues through the adaptive market hypothesis (AMH) that market efficiency evolves over time since markets are not always rational and its participants respond to changes in the aggregate economic environment. Tran and Leirvik (201; 2020) and Hu et al. (2019) note the cryptocurrency market has exhibited long periods of inefficiency with more recent evidence suggesting increased efficiency. As such, several studies have explored aspects pertaining to the cryptocurrency market, such as volatility spillover effects (Omane-Adjepong and Alagidede, 2019; and references therein), comovements of cryptocurrency prices and their volatility (Katsiampa et al. 2019; Omane-Adjepong et al. 2019, and references therein), the interconnectedness among cryptocurrency prices and exchanges (Sifat et al. 2019; Ji et al. 2020; and references therein), along with contagion, herding behavior, and competition within the cryptocurrency market (Antonakakis et al. 2019; Bouri et al. 2019; Fernandez-Villaverde and Sanches, 2019; and references therein).

We extend this literature on the behavior of cryptocurrency markets using the Phillips and Sul (2007) approach to examine convergence behavior of cryptocurrency prices. Drawing upon the early work of Chamberlin and Rothschild (1983) and Connor and Korajczyk (1986; 1988) with respect to common factors in asset pricing models, Phillips and Sul (2007) demonstrate that a time varying multiple common factor structure can be embedded within a time varying single common factor structure.[1] Specific to cryptocurrency prices, the Phillips and Sul (2007) approach captures the evolution of individual cryptocurrency prices in relation to the common component of cryptocurrency prices and an idiosyncratic component, both of which are time-varying. In addition, the Phillips and Sul (2007) modeling approach offers several advantages. First, the Phillips and Sul (2007) approach allows for different time paths as well as individual heterogeneity, unlike the traditional convergence models (β- and σ-convergence) that assume homogeneous characteristics. Second, this approach allows for the endogenous determination of convergence clubs. Third, unlike conventional unit root and cointegration tests, the Phillips and Sul (2007) approach does not impose any particular assumption concerning trend stationarity or stochastic non-stationarity, since it is robust to heterogeneity and the stationarity properties of the variable in question.

In this context, we examine eight major cryptocurrencies in circulation (Bitcoin, Dash, DigiByte, Dogecoin, Ethereum, Litecoin, NEM, and XRP). These sampled cryptocurrencies presently constitute over 80% of the total market capitalization of all the digital currencies in circulation.[2] In addition to exploring the overall panel convergence for the eight cryptocurrency prices, we implement the convergence clustering algorithm of Phillips and Sul (2007) to determine the existence of convergence clubs within the eight cryptocurrencies. Next, we investigate the extent to which cryptocurrencies' market microstructure characteristics explain convergence clubs using an order logit model. The microstructure characteristics include range volatilities, trading volumes, market capitalizations (to proxy for size), number of unique addresses (to proxy for the

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[1] Within the context of the multiple factor model of stock prices set forth by Menzly et al. (2002), Phillips and Sul (2007) show that time varying multiple common factors can be embedded into a time varying single factor framework, see Phillips and Sul (2007, pp. 177-178).

[2] This is noteworthy given that there are almost 2,400 cryptocurrencies in total (see coinmarketcap.com). The eight cryptocurrencies in our sample also constitute over half the total trade volume of all the cryptocurrencies in circulation.

number of users), and mining fees (Akcora et al., 2018; Chaim and Laurini, 2018; Dyhrberg et al., 2018; Vliet, 2018). While range volatility reflects uncertainty about future price changes, trading volume arises from the flow of news and information into the market. Market capitalization reflects size and is generally positively associated with liquidity conditions. The number of addresses reveal network value and, finally, mining fees reflect costs and usage for verifying transactions on the blockchain.

The results reveal the absence of overall panel convergence among the eight cryptocurrency prices. Rather, they show three distinct convergence clubs. The findings from the order logit model reveal that range volatility, market capitalization, and mining fees have a positive and statistically significant impact on convergence behavior, whereas trading volume and addresses each yield a negative and statistically significant influence. These results are important for the following reasons. First, they demonstrate that convergence clubs can emerge among our sampled cryptocurrencies that do not correspond with current technology classifications (or groupings) of cryptocurrencies. Specifically, cryptocurrencies are presently classified as either currencies, protocols, or decentralized applications (dApps) based on what their primary function is, as well as their position within the blockchain technology stack.[3] Second, there is heterogeneity in the role by which various microstructure characteristics play in cryptocurrencies' convergence behaviors. While some microstructure variables may have a positive effect on convergence (range volatility, market capitalization, and mining fees), others have a negative effect (trading volume and number of addresses). **[Insert anything regarding the CBOE result?]**

[3] Corbet et al. (2017) discuss in detail what these technology classifications mean and test whether monetary policy can have a differing effect on each of the cryptocurrencies based on their classification. Deloitte provides an informative visualization and description of the blockchain technology stack here: *https://www2.deloitte.com/content/dam/Deloitte/in/Documents/industries/in-convergence-blockchain-tech-stack-noexp.pdf*.

Section 2 describes the data with the methodology and results reported in Section 3. Concluding remarks are given in Section 4.

2. Data

The analysis requires a sufficient time series on the closing prices of cryptocurrencies in US dollars. For this purpose, we utilize daily data (which includes weekends) for eight cryptocurrencies (Bitcoin, Dash, DigiByte, Dogecoin, Ethereum, Litecoin, NEM, XRP) spanning the time period August 7, 2015 to May 1, 2020, obtained from CoinMarketCap.[4] We focus on eight cryptocurrency closing prices and include a broad set of microstructure variables: range volatility, calculated from high and low prices as $\ln(\text{High}) - \ln(\text{Low})$, trading volume, market capitalization, number of unique addresses, and mining fees. These variables represent fundamental characteristics pertaining to cryptocurrencies' value, risk, and the overall health of their microstructure (Easley, 2019). Table 1 offers summary statistics, while Figure 1 graphically depicts the time series behavior of cryptocurrency closing prices. In terms of the statistics, we can clearly observe the dominance of Bitcoin, not only in terms of closing prices, but also in terms of displaying higher price volatility. This cryptocurrency also exhibits the highest volume of transactions across all cryptocurrencies, while it is also characterized by the highest market capitalization. Moreover, in terms of the skewness statistics, not only in terms of closing prices, but also in terms of the remaining measures, all cryptocurrencies are characterized by the presence of asymmetries, and more specifically are positively skewed. Finally, in terms of the kurtosis

[4] *CoinMarketCap.com* provides historical opening, high, low and closing prices, as well as trade volume and market capitalization data, for all the cryptocurrencies in circulation. This source is advantageous to use since the price data are a volume-weighted average across multiple cryptocurrency market exchanges.

metric, the distribution of the respective cryptocurrencies cannot be characterized as symmetric, since all measures are far from the normal distribution.

[Insert Figure 1 here]

[Insert Table 1 here]

3. Methodology and Results

The Phillips and Sul (2007) modelling approach tests whether there is convergence with respect to the heterogeneous time-varying idiosyncratic components after controlling for a common growth component among the cryptocurrency prices that share the same convergence pattern.[5] Specifically, the Phillips-Sul approach utilizes a time-varying common factor defined as:

$$P_{it} = \delta_{it}\mu_t \tag{1}$$

where i = 1, …, N and t = 1, …, T. P_{it} represents cryptocurrency closing prices. The cryptocurrency closing prices, P_{it}. are comprised of a common component, μ_t, and an idiosyncratic component, δ_{it}, both of which are time-varying. Note the idiosyncratic component, δ_{it}, is a measure of the distance between P_{it} and the common component, μ_t. Phillips and Sul (2007) define the relative transition parameter, h_{it} as follows:

$$h_{it} = \frac{P_{it}}{\frac{1}{N}\sum_{i=1}^{N} P_{it}} = \frac{\delta_{it}}{\frac{1}{N}\sum_{i=1}^{N} \delta_{it}} \tag{2}$$

Equation (2) measures the loading coefficient, δ_{it}, relative to the panel average, hence the transition path for closing prices of cryptocurrency *i* relative to the panel average. In the event the factor loadings, δ_{it}, converge to a constant, δ, then the cross-sectional mean of the relative

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[5] The Phillips-Sul approach does not rely on any assumptions regarding the stationarity of the variables, as in the case for tests of stochastic convergence. Note that prior to the implementation of the Phillips-Sul convergence approach, the trend component of the respective time series for cryptocurrency closing prices is extracted using the Hodrick and Prescott (1997) filter.

transition path for cryptocurrency i, h_{it}, converges to unity and the cross-sectional variation, H_t, of the relative transition path converges to zero as $t \to \infty$:

$$H_t = \frac{1}{N}\sum_{i=1}^{N}(h_{it} - 1)^2 \to 0 \qquad (3)$$

The semi-parametric form of δ_{it} is presented as:

$$\delta_{it} = \delta_i + \frac{\sigma_i \xi_{it}}{L(t)t^{\alpha}} \qquad (4)$$

where δ_i is fixed; $\xi_{it} \sim iid(0,1)$ varies across the closing prices of cryptocurrencies i = 1, 2, …, N; σ_i is an idiosyncratic scale parameter; L(t) is a slow varying function where $L(t) \to \infty$ and $t \to \infty$; and α represents the decay rate (i.e. speed of convergence). Equation (4) states that δ_{it} converges to δ_i for $\alpha \geq 0$. Therefore, the null hypothesis of convergence is $H_0\colon \delta_i = \delta$ and $\alpha \geq 0$ against the alternative hypothesis $H_A\colon \delta_i \neq \delta$ for some i and/or $\alpha < 0$.

In accordance with Phillips and Sul (2007), we set L(t) = logt in the decay model, so the empirical log t regression can be used to test for convergence and the implementation of the clustering algorithm to determine convergence clubs as follows:

$$log\left(\frac{H_1}{H_t}\right) - 2logL(t) = \hat{a} + \hat{b}logt + \varepsilon_t \qquad (5)$$

for t = rT, rT+1, …, T where r > 0 set on the interval [0.2, 0.3]. For $\hat{b} = 2\alpha$, the null hypothesis is considered a one-sided test of $\hat{b} \geq 0$ against $\hat{b} < 0$.[6] To address estimates from Equation (5) that may be weakly time-dependent, heteroskedasticity and autocorrelation consistent standard errors are employed in the least squares estimates of $\hat{b}$.

The Phillips and Sul (2007) procedure uses a clustering algorithm to identify convergence clubs as follows: (1) order the N cryptocurrencies in the panel using the final values of closing prices for the respective cryptocurrencies; (2) starting from the highest-order cryptocurrency in

[6] The speed of convergence is given as $\alpha = \hat{b}/2$.

terms of closing prices, sequentially estimate Equation (5) on the k highest member cryptocurrencies to identify a core group using the cut-off point criterion: $k^* = ArgMax_k\{t_{\hat{b}_k}\}$, subject to $Min_k\{t_{\hat{b}_k}\} > 1.65$, for k = 2, 3, …N; (3) add one cryptocurrency at a time from the remaining cryptocurrencies to the core group, and re-estimate Equation (5) using the sign criterion ($\hat{b} \geq 0$) to determine whether to include a cryptocurrency to the core group; and (4) repeat the above steps iteratively for the remaining cryptocurrencies until convergence clubs can no longer be formed. As a result of this iterative approach, each club formed is associated with its own convergence path.[7]

[Insert Table 2 here]

Table 2 reports the panel convergence results for cryptocurrency closing prices.[8] In Panel A of Table 2 the full panel of eight cryptocurrency closing prices yields a t-statistic of -27.519, which rejects the null hypothesis of overall panel convergence. As such, the clustering algorithm is used to identify distinct convergence clubs. The first club (Club 1) consists of Ethereum and Dash yielding a t-statistic of 1.329, which fails to reject the null hypothesis of convergence. The second club (Club 2) is comprised of Litecoin and NEM with a t-statistic of 1.254, while the third club (Club 3) includes Bitcoin, XRP, Dogecoin, and Digibyte, with a t-statistic of 19.295. These results are important as they show how cryptocurrencies that have different technological classifications **(see footnote 2 should be footnote 3?)** can form clubs. Panel A of Table 2 classifies whether the cryptocurrencies are either currencies (C), protocols (P), or decentralized applications (dApps). Next, to address the possibility of over-estimating the number of clubs, tests for merging adjacent clubs in Panel B of Table 2 clearly reject the null hypothesis of clubs merging.

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[7] Cryptocurrencies that fail to exhibit a convergence pattern are viewed as non-convergent.

[8] Phillips and Sul (2007) suggest that r = 0.3 is a satisfactory selection in terms of both size and power.

The transition paths for the respective convergence clubs are shown in Figures 2A, 2B and 2C, respectively.[9] The speed of convergence, α, varies across the convergence clubs with the cryptocurrency closing prices in Club 1 reaching the convergence reference point of 1 before either Clubs 2 or 3. Club 3, which consists of Bitcoin, Digibyte, Dogecoin and XRP illustrate a tighter convergence during the time when the Chicago Board Options Exchange (CBOE) introduced Bitcoin futures. This is consistent with studies that demonstrate how Bitcoin futures contribute to informational efficiency (Akyildirim, 2019).

[Insert Figures 2A, 2B and 2C here]

Given the convergence clubs identified in Table 2, we explore the role of several microstructure variables in explaining the distinctive convergence clubs using an ordered logit model:

$$y_i^* = X_i\beta + \varepsilon_i \tag{6}$$

where the dependent variable y_i^* is an ordinal value from 1 to 3; X_i represents the set of microstructure variables, and i = 1, 2, …, 8 cryptocurrencies. The column vector β contains the regression coefficients. In Table 3, we find the coefficients for range volatility, market capitalization, and mining fees are each positive and statistically significant, while the coefficients for trading volume and addresses are each negative and statistically significant.

This provides initial evidence for a clientele effect, whereby investors' buying and selling activity (trade volume) and the degree of network activity (addresses) stems from their unique needs, expectations or preferences. Give it has been shown that users may gravitate toward using a particular cryptocurrency for social reasons (Dodd, 2018), it is possible that usage and trading

[9] The transition paths illustrate the tendency of the cryptocurrency prices to converge or diverge from above or below 1, which is the convergence reference point noted by Equation (2).

activity, based on such preferences, can act to segment cryptocurrencies from one another. Since market capitalization is positively related to liquidity, it is likely that the prices of cryptocurrencies with relatively larger liquidity adjust similarly with one another. This notion is consistent with the postulations of Liu and Timmermann (2013), who show that groups of high liquidity stocks should experience similar shifts in their price (thus an acceleration to convergence). Volatility is positively related to convergence since it causes volatility clustering across cryptocurrencies simultaneously. For example, Koutmos (2018) shows how bitcoin's volatility shocks can permeate across a range of cryptocurrencies. Finally, as mining fees decline over time, we expect to see further convergence in cryptocurrency price behaviors.

In terms of the size of our coefficients, a one-unit increase in range volatility, market capitalization, and mining fees each translate to an increased likelihood of joining Club 1 moving from Clubs 2 and 3, or Club 2 moving from Club 3, with these probabilities being 0.479, 0.488, and 0.203, respectively. In contrast, a one-unit increase in trading volume and addresses each lead to a decreased likelihood of joining Club 1 moving from Clubs 2 and 3, or Club 2 moving from Club 3, with these probabilities being 0.656 and 0.224, respectively.

[Insert Table 3 here]

4. Concluding Remarks

The market for cryptocurrencies has risen steadily over the last few years following the inception of Bitcoin. In this study, we explore the convergence behavior of eight major cryptocurrencies. We provide a framework for evaluating the role of microstructure variables serve in the convergence behavior of cryptocurrency closing prices. First, we show convergence is possible between cryptocurrencies with distinct technological functions. Second, market microstructure behavior drives convergence. Our results show initial support for a clientele effect in convergence behavior. We also show how the introduction of futures markets can cause convergence to shift among cryptocurrencies. From an econometric standpoint, our empirical approach is tractable and can accommodate a wide range of idiosyncratic or systematic variables to further test nuances that may exist in the convergence and divergence patterns of these new digital assets.

Figure 1
Time Series Plots of Cryptocurrency Closing Prices

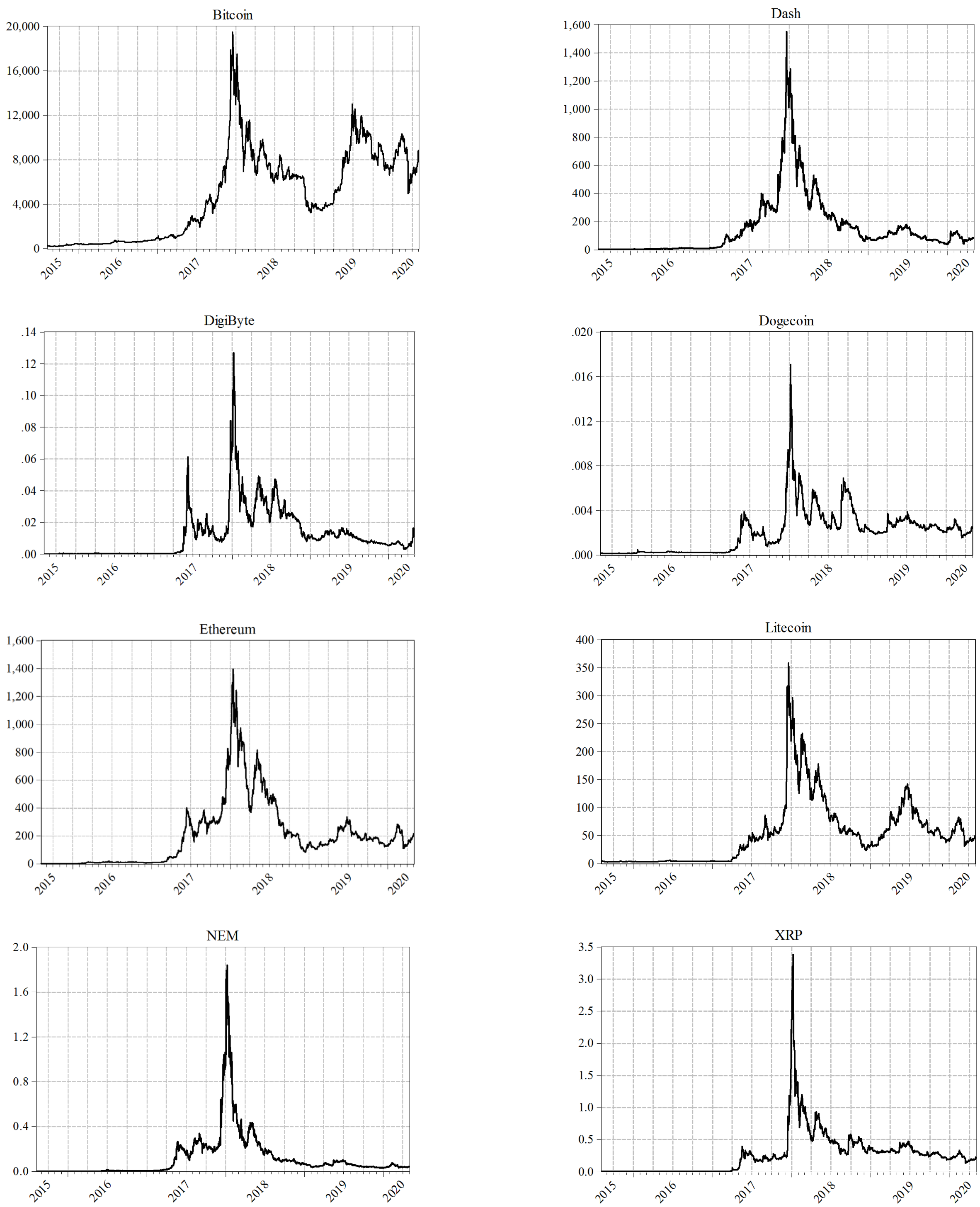


Table 1
Summary Statistics

Variables	Mean	Std. Dev.	Min.	Max.	Skew.	Kurt.
Bitcoin						
Price	4,714.63	3,966.83	210.49	19,497.40	0.60	-0.31
Range volatility	0.05	0.04	0.00	0.49	2.69	13.19
Trading volume	7.93E+10	1.11E+10	1.27E+07	7.42E+10	1.88E+00	3.52E+00
Market cap.	8.17E+10	6.95E+10	3.06E+05	3.27E+11	5.34E-01	-5.82E-01
# of addresses	6.44E+05	1.69E+05	2.53E+05	1.29E+06	3.33E-01	5.59E-01
Mining fees	5.98E+05	1.72E+06	4.48E+03	2.14E+07	6.08E+00	4.29E+01
Dash						
Price	151.95	213.53	2.06	1,550.85	2.76	9.12
Range volatility	0.08	0.07	0.01	1.58	7.67	127.20
Trading volume	1.59E+08	2.34E+08	1.84E+04	2.74E+09	3.11E+00	1.56E+01
Market cap.	1.22E+09	1.67E+09	1.24E+07	1.20E+10	2.70E+00	8.81E+00
# of addresses	4.19E+04	3.11E+04	5.28E+03	2.67E+05	1.20E+00	3.70E+00
Mining fees	7.97E+02	1.71E+03	2.21E+00	1.94E+04	4.14E+00	2.14E+01
DigiByte						
Price	0.01	0.02	0.00	0.13	2.63	10.72
Range volatility	0.12	0.11	0.02	1.38	4.02	28.98
Trading volume	4.89E+06	1.60E+07	2.20E+02	2.32E+08	8.21E+00	8.51E+01
Market cap.	1.24E+08	1.54E+08	2.18E+05	1.23E+09	2.41E+00	9.28E+00
# of addresses	1.96E+04	1.69E+05	1.81E+03	4.31E+06	2.07E+01	4.62E+02
Mining fees	4.91E+00	1.43E+01	5.20E-04	2.25E+02	6.39E+00	5.83E+01
Dogecoin						
Price	2.00E-03	2.00E-03	1.10E-04	0.02	1.97	7.47
Range volatility	0.08	0.07	0.01	0.61	2.95	12.15
Trading volume	2.65E+07	4.44E+07	1.67E+04	2.99E+08	2.70E+00	8.50E+00
Market cap.	2.34E+08	2.27E+08	1.16E+07	1.93E+09	1.82E+00	6.61E+00
# of addresses	4.85E+04	2.53E+04	1.34E+04	3.38E+05	1.91E+00	1.19E+01
Mining fees	8.66E+01	1.10E+02	1.49E+00	1.41E+03	3.87E+00	2.92E+01
Ethereum						
Price	202.55	234.85	0.44	1396.42	1.88	4.02
Range volatility	0.08	0.07	0.01	1.37	4.96	60.23
Trading volume	3.24E+09	4.80E+09	1.02E+05	2.81E+10	2.19E+00	5.30E+00
Market cap.	2.03E+10	2.30E+10	3.22E+07	1.35E+11	1.79E+00	3.70E+00
# of addresses	2.15E+05	3.18E+05	1.11E+03	7.16E+06	1.14E+01	1.96E+02
Mining fees	1.46E+05	3.64E+05	4.27E+00	4.55E+06	6.33E+00	5.09E+01

Table 1
Summary Statistics (Cont.)

Variables	Mean	Std. Dev.	Min.	Max.	Skew.	Kurt.
Litecoin						
Price	52.39	56.83	2.63	358.34	1.82	4.23
Range volatility	0.06	0.06	0.01	0.54	2.93	13.70
Trading volume	1.06E+09	1.55E+09	5.07E+05	7.55E+09	1.53E+00	1.30E+00
Market cap.	3.03E+09	3.21E+09	1.11E+08	1.95E+10	1.59E+00	3.15E+00
# of addresses	6.28E+04	6.02E+04	7.15E+03	6.02E+05	3.24E+00	1.76E+01
Mining fees	3.15E+03	1.28E+04	3.75E+01	2.34E+05	1.03E+01	1.36E+02
NEM						
Price	0.12	0.21	0.00	1.84	4.12	21.57
Range volatility	0.10	0.09	0.01	1.10	2.98	16.76
Trading volume	1.66E+07	2.80E+07	6.91E+01	3.32E+08	4.78E+00	3.52E+01
Market cap.	1.04E+09	1.88E+09	7.71E+05	1.66E+10	4.12E+00	2.16E+01
# of addresses	2.03E+03	3.19E+03	6.00E+00	6.41E+04	1.01E+01	1.57E+02
Mining fees	7.91E+02	2.28E+03	4.90E-02	3.10E+04	6.39E+00	5.59E+01
XRP						
Price	0.27	0.34	0.00	3.38	3.60	21.03
Range volatility	0.07	0.08	0.00	1.19	4.77	38.81
Trading volume	6.71E+08	1.03E+09	2.48E+04	9.42E+09	3.03E+00	1.45E+01
Market cap.	1.07E+10	1.34E+10	1.37E+08	1.31E+11	3.45E+00	2.00E+01
# of addresses	6.35E+03	1.09E+04	6.14E+02	2.32E+05	1.03E+01	1.58E+02
Mining fees	1.08E+03	4.50E+03	3.34E+00	1.11E+05	1.35E+01	2.59E+02

Table 2
Convergence Tests for Cryptocurrency Closing Prices

Panel A: Full Panel of Cryptocurrency Closing Prices (N = 8)

Subgroup	Cryptocurrencies	b coefficient	log t-statistic	Convergence Speed, α
Full sample	Bitcoin (C), Ethereum (P), XRP (dApp), Litecoin (C), Dash (C), NEM (P), Dogecoin (C), DigiByte (P)	-0.496	-27.519***	
Club 1	Ethereum (P), Dash (C)	1.994	1.329	0.997
Club 2	Litecoin (C), NEM (P)	0.208	1.254	0.104
Club 3	Bitcoin (C), XRP (dApp), Dogecoin (C), DigiByte (P)	0.462	19.295	0.231

Notes: ***: $p \leq 0.01$, denotes rejection of the null hypothesis of convergence. The parentheses indicate whether the cryptocurrency is classified as a currency (C), protocol (P), or decentralized application (dApp).

Panel B: Tests of merging clubs

Merging clubs	t-statistic	p-value
Club 1 + 2	6.836***	0.00
Club 2 + 3	7.105***	0.00

Notes: ***: $p \leq 0.01$ and indicates rejection of then null hypothesis of clubs merging.

Figure 2A
Convergence Club 1

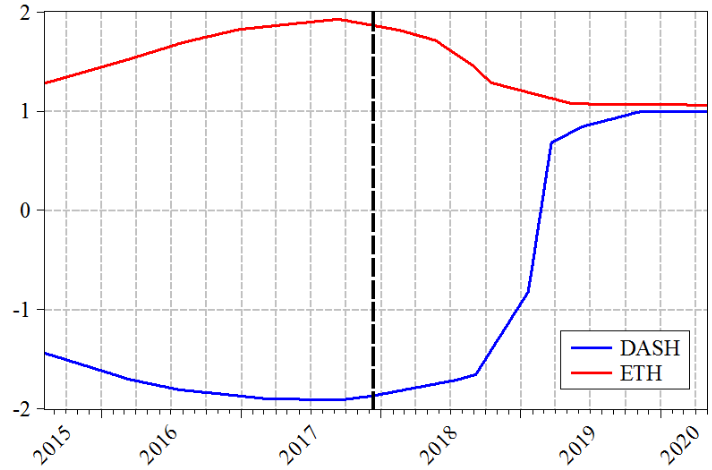


Figure 2B
Convergence Club 2

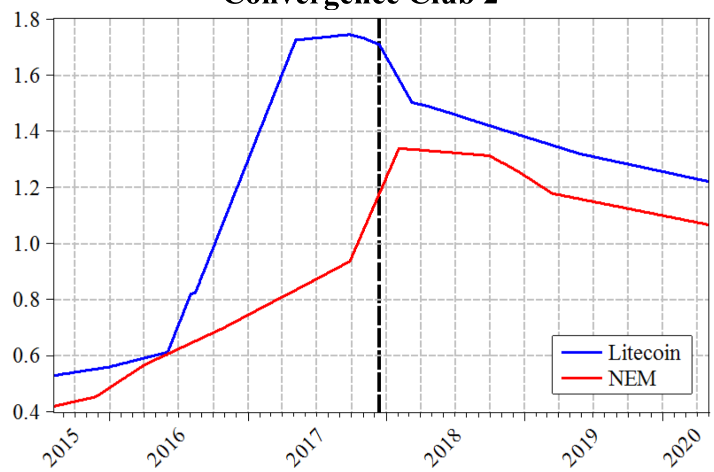
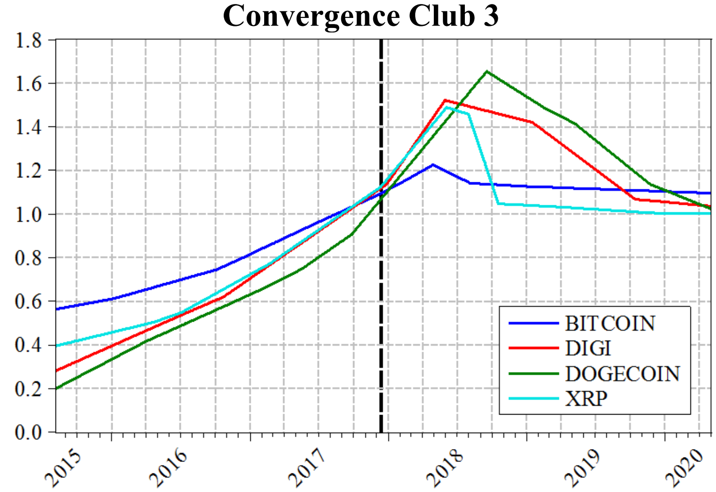


Figure 2C
Convergence Club 3



Notes: The vertical black dashed line corresponds to the date December 10, 2017, when the Chicago Board Options Exchange (CBOE) offered the first bitcoin futures contract.

Table 3
Order Logit Model Results

Variables	Coefficient	p-value
Range volatility	0.479***	0.00
Trading volume	-0.656***	0.00
Market cap.	0.488***	0.00
# of addresses	-0.224**	0.02
Mining fees	0.203**	0.03
Pseudo R^2 = 0.57		

Note: ***: p≤0.01; **: p≤0.05.

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