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Altcoins as Alternatives for What?

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Abstract

This paper uses a time-series data for altcoins to see correlations among these altcoins and Bitcoin (BTC), Euro (EUR), Japanese Yen (JPY), and Chinese Yuan (CNY). The dataset is a dynamic panel data (unbalanced) gathered from an online content (https://coinmarketcap.com/currencies/views/all/) that provides real-time market data for more than 600 cryptocurrencies, but the data is not stored. To store the data, I had my research assistant access the web site almost everyday at a certain time between October 29, 2015 and December 24, 2015. The collected data consists of 13,407 total observations with 540 altcoins and Bitcoin. For lag-2 regressions, effectively 359 altcoins with 7,402 observations are available. For the analysis, we employ a nested dynamic model (a la simultaneous equations model) that controls endogeneity. The model is estimated by 2SLS. We then find that altcoins of larger market capitalizations (major altcoins) are positively correlated with EUR and negatively with CNY. Equivalent results are also obtained in the pooled regression model that uses a weight for BTC price based on relative market capitalization to treat altcoins of smaller market capitalizations (minor altcoins) as major ones. The weight is applied in order to adjust prices of altcoins to BTC price since they vary from few dollars to less than pennies. The regression for Bitcoin price also shows similar results: siginificantly positive correlation with EUR and negative with CNY. On the other hand, we also find that minor coins are negatively correlated with BTC. The results suggest that BTC is a substitute for minor altcoins and EUR and CNY are a complement and a substitute for major ones. In the analysis, major and minor altcoins are classified by a structural breaking test. Identification tests, unit-root tests, and cointegration tests are provided for all regressions. In addition, heteroskedasticity is also considered and controled.

1 Introduction

Bitcoin has launched by a cryptographer community in 2008 using an idea provided by Satoshi Nakamoto [20] distributed among information engineers through their mailing list. Initially, Bitcoin was just a kind of game among "geeks", but currently one of the core technology of innovations in the finance industry (FinTech). In addition, some altcoins (cryptocurrencies other than Bitcoin) are also getting their presence in the FinTech movement, as Etherium. This study investigates how altcoins are priced in terms of Bitcoin and some staple currencies.

Although there are several arguments regarding moneyness of Bitcoin (for example, Selgin [21]), especially after the banking crisis in Cyprus in 2013, Bitcoin has started getting some power rapidly. At the same time, the value of Bitcoin has jumped up from a penny to more than $1,200 in 2014. During these periods, Bitcoin has also experienced several troubles such as Mt.Gox and Silk Roads, but it continues expanding in as a method of payment or as a public ledger in broad. The value of Bitcoin was always affected largely by such incidents, but the price of Bitcoin recovered after them again and again.[1] In 2015, it seems that Bitcoin has obtained some presence in the financial industry as a financial asset.

There are polarized discussions regarding the rise of Bitcoin as bubble. Actually, most of empirical investigations on Bitcoin market focus on bubbles. For example, even some recently published studies, such as Cheah [4] and Cheung *el. al.* [5], claim that there are several signs of bubbles in Bitcoin market. Yet, Bitcoin is still alive since 2009 and the value is reaching $500 at the beginning of 2016. In addition, there is no reason to say an object of no intrinsic value cannot be money (such an object is called *fiat money*). An object obtains its value so long as it is useful—for example, Polasik *et. al.* [17] verifies the pricing mechanism of Bitcoin from this viewpoint.

Many studies on pricing mechanism whose focuses are not bubbles focus on mining. Having larger body of miners means shorter approval time for each transaction and that may increase its value. In addition, altcoins are often used to get Bitcoins. Larger body of miners then means larger chance of exchange and that will also increase its value, as well. Miners are more attracted by altcoins of less mining difficulty with higher value.

The focus of this study is also the pricing mechanism to find out currencies inclusive of Bitcoin that statistically significantly affect values of altcoins. In this study, the main focus is placed on a time-series relationship among crypto- and traditional currencies instead of bubbles and mining. Ong *et. al.* [15] tries to figure out potentials of 440 altcoins. Their sophisticated study explores altcoins inclusive of mining and security matters utilizing social network data. Usually, blighter future induces higher price and Dwyer [7] actually discusses valuation of cryptocurrency with those aspects. Such aspects are assuredly important to consider pricing mechanism especially at the beginning of each altcoin. However, altcoins become financial assets once they obtain value; thence, we need to consider relationship among altcoins and other financial assets as this paper tries while no study does. Gandal and Halaburda [8] considers competitions among altcoins. They find out that Bitcoin is the giant that exploits the network effect as medium of exchange and as store of value. If Bitcoin is merely a medium of exchange, the network effect will drive out altcoins. In other words, no altcoin can survive if it is merely a medium of exchange. But, Bitcoin does not take all and some altcoins are maintained, as financial assets. Similarly, Bornholdt and Sneppen [2] suggest the survival of cryptocurrencies, which determines its value, is determined by a voting scheme. Hayes [11] further argues cryptographical system is another determinant of the pricing scheme. In his argument, these factors generate values of altcoins. From the valuation mechanism, he tries to predict emergence patterns of new altcoins.

Even if most of altcoins are marginal substances at this time, all currencies, inclusive of crypto and traditional, are networked through the market. It is a well-known phenomenon that such a small shock may generate a credit restriction to magnify the initial negative impact to further create the crisis, *á la* Kiyotaki and Moore [14]. Identifying

[1] Regulations against illicit activities may not necessarily negatively affects the value of Bitcoin since regulations may increase varieties of illicit goods to generate taste-of-variety effect (Saito [19]).

Table 1: Correlations among key currencies

	BTC	EUR	JPY	CNY
BTC	1.0000	—	—	—
EUR	0.3813	1.0000	—	—
JPY	0.3533	0.7766	1.0000	—
CNY	−0.6895	−0.1111	−0.2010	1.0000

key currencies that affect altcoins has some importance to understand potential risks of crises. In particular, the altcoins may vanish if a key currency moves largely to negatively affect values of those altcoins. In theory, Houy [13] argues that a mining game may not be sustainable if rewards largely decline. Halting the mining game implies the end of the cryptocurrency. Similarly, Saito [18] shows that a negative shock may drive out even stable equilibrium.[2] In reality, behind emergence of several new altcoins, several others vanish without being noticed.

Besides the steady growth of Bitcoin, though Ripple stopped their "service", altcoins such as Litecoin, Dogecoin, and the likes also continue growing. Some of them already obtain some recognitions in the cryptocurrency market. For example, Litecoin is valued around \$3 in the beginning of 2016. Behind the scenes of the altcoin growth, what we need to know is that there are lots of Chinese participants other. The presence of Chinese traders in the cryptocurrency market sometimes affect their prices. Actually, CoinTelegraph reports there were massive in-flow of Litecoin from China to move the market in July 2015.[3] A result of this paper will confirm the presence of those Chinese players.

The discussion is delivered as follows. Section 2 summarizes the data and introduces the empirical strategy. Section 3 provides statistical analyses (technical) to proceed further investigations in Section 4 to conclude in Section 5. In this paper, statistical significance levels at 1%, 5%, and 10% are indicated by **, *, and †, respectively.

2 Dataset and Regression Model

The dataset is a dynamic panel data (unbalanced) gathered from an online content.[4] The online content provides real-time market data for more than 600 cryptocurrencies, but the data is not stored. To store the data, I had my research assistant access the web site almost everyday at a certain time between October 29, 2015 and December 24, 2015. The collected data consists of 13,407 total observations with 540 altcoins and Bitcoin. The information of each sample consists of date t, cryptocurrency identifier $i \in \Theta$, market capitalization $C_{i,t}$, cryptocurrency stock $S_{i,t}$, and price $P_{i,t}$. In this dataset, the price is identically equal to the market capitalization divided by the stock: $C_{i,t} \equiv P_{i,t} S_{i,t}$. All pecuniary values are measured in US dollars (USD).

In addition to information in the cryptocurrency data, the author retrieved additional information from the Pacific Exchange Rate Service maintained by the University of British Columbia to add exchange rates in USD for euros (EUR), Japanese yens (JPY), and Chinese yuans (CNY). Among these currencies, EUR is included as it is the second axis currency, JPY as it is a *de facto* substitute for other key currencies, and CNY as China is one of major players in the cryptocurrency market. We could include some other currencies in exchange for efficiency of estimation, but small currencies are likely correlate to major currencies such as EUR, JPY, and CNY and that implies there is no gain to compensate for the efficiency loss sufficiently.

The dataset consists of a series of USD prices (exchange rates) of altcoins (ALT). The price is naturally endogenously determined by previous prices to bring endogeneity problems. In order to resolve such problems, we consider

[2] A similar argument focusing on the attitude of the government is also made by Hendrickson *et. al.* [12].
[3] http://cointelegraph.com/news/114809/chinese-pump-n-dump-suspected-as-litecoin-passes-bitcoin-in-trading-volume
[4] The URL of the data source is: https://coinmarketcap.com/currencies/views/all/

a structure of pricing system as simultaneous equations model assuming that daily rates conform to a Poisson process; hence, $Cov[P_{i,t}, P_{i,s}] = 0$, $Cov[P_{i,t}, P_{1,s}] = 0$, and $Cov[P_{1,t}, P_{1,s}] = 0$ for all t and $s \leq t-2$.

Let $J = \{EUR, JPY, CNY\}$ be the set of chosen exchange rates, $p_{i,t} \equiv \ln P_{i,t}$ be the logarithm of USD price. Let $i = 1$ be the identifier for BTC. Let $\varepsilon_{i,t}$, $\eta_{i,t}$, and $\mu_{i,t}$ be errors of corresponding equations. Let ϕ_i be the fixed effect. Considering efficiency of estimation, the structural equation system is provided as a nested model:

$$\begin{cases} p_{i,t} = \beta_0 + \beta_{ALT} p_{i,t-1} + \beta_{BTC} \omega_i p_{1,t-1} + \sum_{j \in J} \beta_j p_{j,t-1} + \phi_i + \varepsilon_{i,t} \\ p_{i,t-1} = \alpha_i + \alpha_i p_{i,t-2} + \alpha_{BTC} \omega_{i,t-2} p_{1,t-2} + \sum_{j \in J} \beta_j p_{j,t-1} + \eta_{i,t} \\ \omega_i p_{1,t-1} = \gamma_i + \gamma_i p_{i,t-2} + \gamma_{BTC} \omega_{i,t-2} p_{1,t-2} + \sum_{j \in J} \gamma_j p_{j,t-1} + \mu_{i,t} \end{cases}, \tag{1}$$

where ω_i in the regression model is

$$\omega_i = \begin{cases} \frac{1}{T} \sum_{t=1}^{T} \frac{C_{i,t}}{C_{1,t}} & \text{(if weighted)} \\ 1 & \text{(if not weighted)} \end{cases}. \tag{2}$$

This parameter adjust the nominal price for smaller altcoins compared with BTC when $\omega_i \neq 1$, so that it is useful especially in a pooled regression.

When it is weighted, ω_i is the average of relative market capitalization *vis-á-vis* Bitcoin (BTC) that indicates a relative importance of each cryptocurrency in the market. The next proposition clarifies the interpretation of $\omega_i \beta_{BTC}$ in the weighted case.

Proposition 1 *In the weighted model, the partial elasticity of ALT i's USD price in response to BTC's USD price, $e_{i,t}$, is approximately computed as $e_i = \omega_i \beta_{BTC}$ as time independent when T is sufficiently large.*

Proof. See Appendix A. ■

In order to derive inferences to justify the use of the cross term $\omega_i p_{i,t}$, let us suppose T is sufficiently large. Proposition 1 then shows that prices of minor altcoins are supposed to be less reactive to the price of BTC compared with major ones. Actually, minor altcoins are not interested by investors that make investment on BTC and its relevant business. Altcoins are interested by users of specific community. For example, it is an extreme case though, CoinDesk reports that an altcoin named Unete was designed to produce a pyramid scheme.[5] As usual, even if it is not designed to be a pyramid scheme, minor coins are supported by enthusiastic users. These users do not sell "their" coins in exchange for getting other major ones such as BTC. However, for another example, users of major altcoins, such as Litecoin (LTC) users, may sell their litecoins if LTC price increases relative to BTC, as BTC may have blighter future. Thence, e_i will get smaller as the presence of the ALT gets smaller in the cryptocurrency market, as expressed by $\omega_i \beta_{BTC}$.

It should be noted here that T may not be sufficiently large as considered by Proposition 1; whence, the interpretation of $\omega_i \beta_{BTC}$ cannot be accurate to be time-independent, as e_i. For instance, in such cases, e_i becomes time-dependent:

$$e_{i,t} = \frac{\omega_i \beta_{BTC} + T^{-1} C_{i,t-1}/C_{1,t-1}}{1 - T^{-1} C_{i,t}/C_{1,t}}. \tag{3}$$

[5]http://www.coindesk.com/police-arrest-20-in-digital-currency-pyramid-scheme/

Table 2: Unit-root tests with lag = 2 (H_0: variable has unit root)

		$p_{i,t}$	$\omega_i p_{1,t}$	$p_{1,t}$	$p_{EUR,t}$	$p_{JPY,t}$	$p_{CNY,t}$
ADF	test statistic	3.9917	19.53	−0.5076	−1.0337	0.3049	−0.8381
	p-value	1.0000	1.0000	0.8905	0.7408	0.9776	0.8077
PP	test statistic	−20.43	−19.57	−2.4113	−0.5957	−0.5125	−0.1948
	p-value	0.0000	0.0000	0.1386	0.8719	0.8895	0.9391

Yet, it is still true that prices of minor altcoins are less reactive to BTC price compared with major ones, as a decrease in relative market capitalization at any period s, $C_{i,s}/C_{1,s}$, reduces ω_i and so does $e_{i,s}$. Thus the relationship between ω_i and $e_{i,t}$ is not altered by T. In the estimation, where T is unlikely large enough, using $\omega_i p_{1,t-1}$ brings an endogeneity problem, as treated by the third equation in (1).

3 Statistical Results

3.1 Unit-Root Tests

To begin with, unit-root tests are processed using Fisher type augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests for the unbalanced dynamic panel data $p_{i,t}$ and $\omega_i p_{i,t}$, and ordinary ADF and PP tests for the price of BTC and exchange rates of national currencies. The results with two-period lag are shown in Table 2. The test statistics for ADF and PP in the Fisher type tests are inverse normal Z statistics and those for ordinary ADF and PP are t values. The use of inverse normal Z statistic is based on the simulation-based argument by Choi [6] that suggests the use of Z test performs the best when the sample size is not sufficiently large—actually, our dynamic panel data consists of 7,402 effective observations under two-period lag model while there are more than 359 effective groups to provide 20.62 samples per group on average.

All results from ADF tests in Table 2 cannot reject the null hypothesis; hence, all variables will have unit roots. Yet, the results from PP in the dynamic panel data polarize the ADF outcomes by rejecting the null hypothesis at 0.0000 significance level. An argument of Campbell and Perron [3] resolves this problem. In particular, PP test of high power may incorrectly rejects the null hypothesis of unit root when the sample size is small. In such cases, we may need to refer other test result as ADF. As noted above, the average sample size is 20.62 and that implies that PP may have rejected the null hypothesis incorrectly, as ADF tests cannot reject it at 1.0000 significance level. So, let us rely on the ADF results for the dynamic panel variables to process time-series regressions.

3.2 Bitcoin

Prior to looking at altcoins, for later use, a regression result for BTC is provided:

$$\underset{(s.e.)}{p_{1,t}} = -\underset{(7.8671)}{13.19} + \underset{(0.0803)}{0.6267^{**}} p_{1,t-1} + \underset{(0.8646)}{1.6684^{\dagger}} p_{EUR,t-1} - \underset{(1.4685)}{1.1912} p_{JPY,t-1} - \underset{(1.3768)}{5.1430^{**}} p_{CNY,t-1} + \varepsilon_{1,t}. \tag{4}$$

The sample size of this regression is 41 and R^2 is 0.8535. The test statistics for Breusch-Pagan and RESET tests are $\chi^2(1) = 0.27$ and $F(3,33) = 1.11$, respectively; hence, heteroskedasticity and misspecification are not identified at 0.6006 and 0.3585 significance levels, respectively. The Engel-Granger cointegration tests for (4) are shown in Table 3. According to this table, ADF fails to reject the null hypothesis when lags are larger than 2 at 5% level while PP successfully rejects the null hypothesis for all lags. Another argument in Campbell and Perron [3] suggests the solution. ADF is a parametric method that is highly dependent on lags while PP is a nonparametric approach that is

Table 3: Cointegration tests for BTC price (H_0: error term has unit root)

	lags	0	1	2	3	4
ADF	test statistic	-7.0504	-3.5856	-2.4985	-2.8186	-2.1939
	p-value	0.0000	0.0060	0.1158	0.0557	0.2085
PP	test statistic	-7.0504	-7.0494	-6.9871	-6.9688	-6.9651
	p-value	0.0000	0.0000	0.0000	0.0000	0.0000

less dependent on them. It is thus known that ADF may change test results depending on lags when sample size is small. In addition, ADF fails to reject the null hypothesis in our model for some lags, but it is not at extremely high significance level. Thus, it is not harmful to conclude that the error does not have unit root (no cointegration) and regression (4) does not show a spurious correlation.

3.3 Altcoins (Pooled)

The results inclusive of all effective altcoins are provided in Table 4 (reporting common and individual constants is omitted). In this table, "weighted" and "nominal" indicate whether BTC price is weighted; hence, ω_i is relative market capitalization in the weighted model and $\omega_i \equiv 1$ in the nominal model. For clarity, let us note that the OLS uses only the first equation of system equations (1), so that, allowing abuse of notation β's, the OLS model is

$$p_{i,t} = \beta_0 + \beta_{ALT} p_{i,t-1} + \beta_{BTC} \omega_i p_{1,t-1} + \sum_{j \in J} \beta_j p_{j,t-1} + \phi_i + \varepsilon_{i,t}, \tag{5}$$

and the reduced form is

$$p_{i,t} = \beta_0 + \beta_{ALT} p_{i,t-2} + \beta_{BTC} \omega_i p_{1,t-2} + \sum_{j \in J} \beta_j p_{j,t-1} + \phi_i + \varepsilon_{i,t}. \tag{6}$$

In the reduced form model, $p_{i,t-2}$ and $\omega_i p_{1,t-2}$ replace $p_{i,t-1}$ and $p_{1,t-1}$ in the OLS model, respectively.

Figure 1 shows scattered plots for linear estimates and errors for 2SLS regressions. The two plots seem to show existence of heteroskedasticity and then robust standard errors are applied to test the significance of coefficients in Table 4. For further investigations, Table 5 shows the difference between nominal and robust standard errors for each coefficient in each model. The difference between the two standard errors is shown by the last row for each model. If the value is apart from unity, influence of heteroskedasticity is suspected. According to Table 5, we can confirm the influence of heteroskedasticity on β_{ALT} in both models and on β_{BTC} in "weighted" model.

Using robust standard errors, Table 6 shows if each model is adequately identified and each endogenous variables is adequately chosen. The test statistics for underidentification and endogeneity tests are $\chi^2(1)$ and $\chi^2(2)$, respectively. The obtained statistic values are sufficiently large to reject null hypotheses. The critical value for the weak identification test follows Stock and Yogo [22]. The obtained value is out of range of the provided table, but it is far above the 5% critical value to reject the null hypothesis. Thus 2SLS models are neither underidentified nor weakly identified. In addition, endogenous variables are not treated as exogenous. These results indicate that using 2SLS is more preferable than using OLS and reduced form models.

Next, we consider the Engel-Grenger cointegration tests for the predicted errors in the two 2SLS models. For the cointegration test, we use nominal errors even if they exhibit heteroskedasticity. Existence of heteroskedasticity may affect the ADF result by over rejecting null hypothesis, but it is also known that using normal distribution will be enough in practice (for example, Hansen [10] and Hamori and Tokihisa [9]). In addition, Phillips-Perron test is robust

Table 4: Regression results (robust s.e.)

	2SLS		OLS		reduced form	
	weighted	*nominal*	*weighted*	*nominal*	*weighted*	*nominal*
β_{ALT}	0.8848^{**}	0.8837^{**}	0.7329^{**}	0.7472^{**}	0.6571^{**}	0.6721^{**}
(s.e.)	(0.0207)	(0.0207)	(0.0196)	(0.0200)	(0.0176)	(0.0183)
β_{BTC}	-0.7442	-0.0185	-1.5510	-0.2335^{**}	-2.1468	-0.2123^{**}
(s.e.)	(2.2578)	(0.0420)	(4.2466)	(0.0228)	(3.6917)	(0.0290)
β_{EUR}	0.5226^{*}	0.4565	1.0465^{**}	1.7156^{**}	1.7168^{**}	2.4308^{**}
(s.e.)	(0.2753)	(0.2921)	(0.2033)	(0.1940)	(0.2897)	(0.2978)
β_{JPY}	0.2053	0.2476	-0.5577	$-0.6602^{\dagger}$	-1.1384^{*}	-1.5502^{**}
(s.e.)	(0.4549)	(0.4570)	(0.3443)	(0.3395)	(0.5155)	(0.5156)
β_{CNY}	-0.8634^{**}	-0.6562	-0.5978^{*}	-3.0933^{**}	-1.0123^{*}	-3.1201^{**}
(s.e.)	(0.3309)	(0.5809)	(0.4575)	(0.5340)	(0.4065)	(0.5010)
R^2	0.5622	0.5622	0.5687	0.5742	0.4675	0.4724
obs.	7,402	7,402	9,755	9,755	7,402	7,402
altcoins	359	359	459	459	359	359

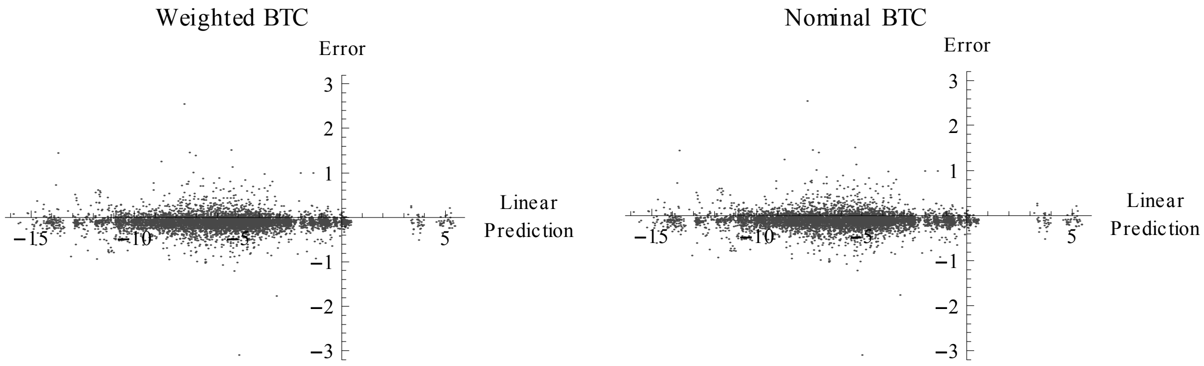

Figure 1: Linear prediction and errors

Table 5: Identification and endogeneity tests for 2SLS

	weighted logarithm BTC price				
	β_{ALT}	β_{BTC}	β_{EUR}	β_{JPY}	β_{CNY}
(1) nominal s.e.	0.0105	7.5791	0.2625	0.4732	0.3582
(2) robust s.e.	0.0203	2.2578	0.2753	0.4549	0.3309
(1)/(2)	0.5181	3.3569	0.9535	1.0402	1.0825
	nominal logarithm BTC price				
(1) nominal s.e.	0.0105	0.0395	0.2979	0.4814	0.5586
(2) robust s.e.	0.0207	0.0420	0.2921	0.4570	0.5809
(1)/(2)	0.5077	0.9396	1.0198	1.0534	0.9615

Table 6: Identifications and endogeneity tests for 2SLS

		weighted	nominal
underidentification test	test statistic	476.109	778.891
(H_0: model is underidentified)	p-value	0.0000	0.0000
weak identification test	test statistic	1226.563	1901.987
(H_0: model is weakly identified)	p-value	—	—
endogeneity test	test statistic	46.397	89.271
(H_0: endogenous regressors are treated as exogenous)	p-value	0.0000	0.0000

Table 7: Cointegration tests for 2SLS (H_0: error term has unit root)

	weighted logarithm BTC price					
	lags	0	1	2	3	4
ADF	test statistic	−78.93	−43.03	−23.41	−16.93	−6.764
	p-value	0.0000	0.0000	0.0000	0.0000	0.0000
PP	test statistic	−78.93	−80.19	−81.83	−83.26	−84.51
	p-value	0.0000	0.0000	0.0000	0.0000	0.0000
	nominal logarithm BTC price					
ADF	test statistic	−78.96	−43.01	−23.02	−16.59	−6.222
	p-value	0.0000	0.0000	0.0000	0.0000	0.0000
PP	test statistic	−78.96	−80.27	−81.89	−83.35	−84.61
	p-value	0.0000	0.0000	0.0000	0.0000	0.0000

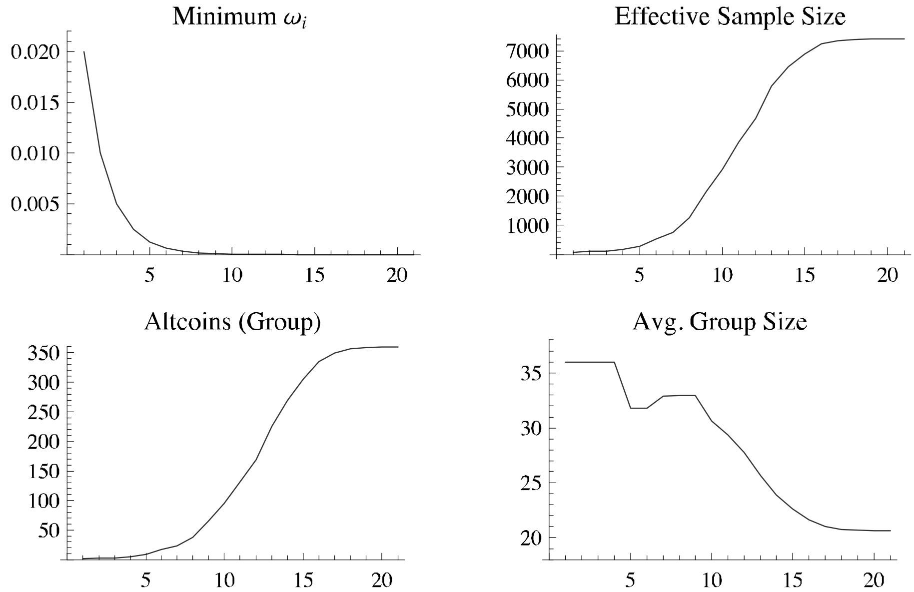

Figure 2: Key numbers for each regression by class

against heteroskedasticity (Phillips and Perron [16]). Thus ADF and PP are simultaneously tested for lags between 0 and 4, as shown in Table 4. According to this table, there is no sign of cointegrations and the two models are not showing spurious correlations.

3.4 Altcoins (Separated)

Impacts of each parameter may differ by types of altcoins. In this section, altcoins are classified by the relative market capitalization ω_i. Each class $k = 1, \ldots, 21$ defines a subset of altcoins $\Theta_k \subseteq \Theta$ such that

$$\Theta_k = \left\{ i \in \Theta | \omega_i \geq 0.02 \times 0.5^{k-1} \right\}. \tag{7}$$

The threshold value of ω_i, effective sample size, number of altcoins in Θ_k, and average group size for each k (horizontal axis) are shown in Figure 2.

Applying the same procedures as 2SLS regressions in Section 3.3 for each k, we obtain estimates and correspond-

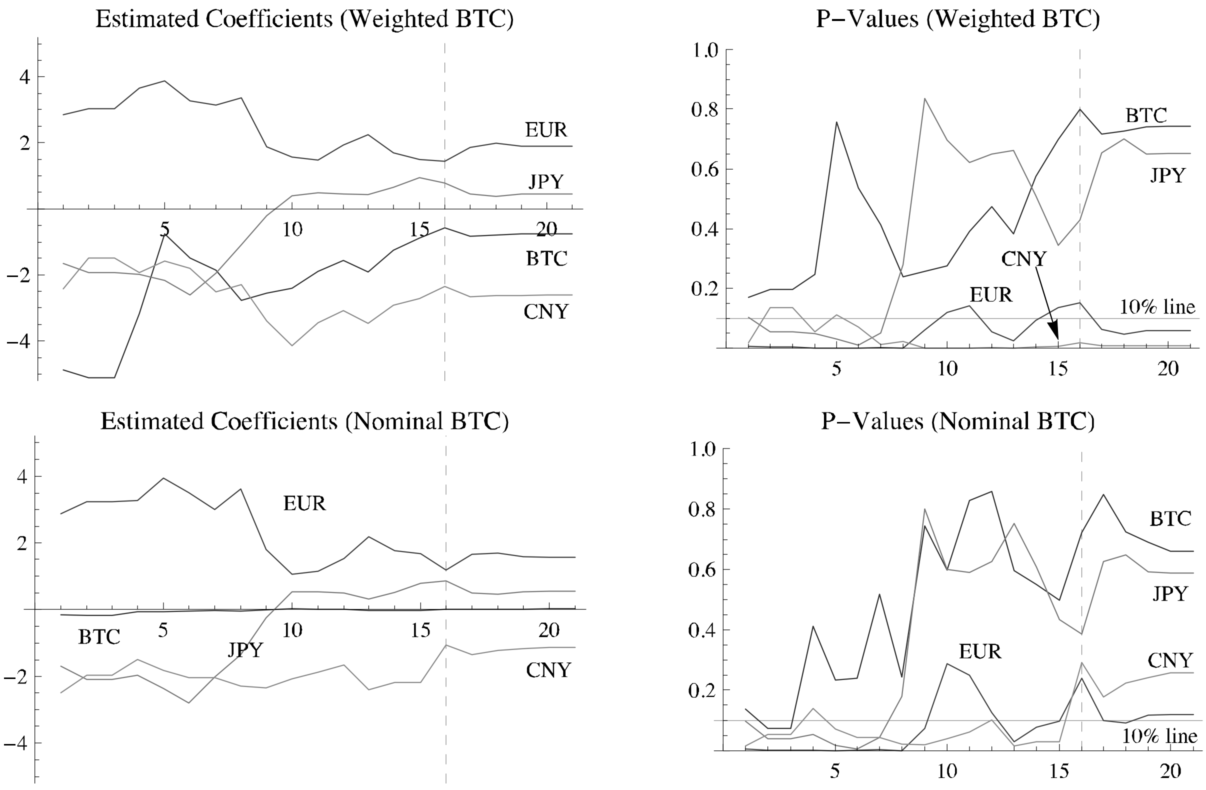

Figure 3: Regression results for the upper class: $i \in \Theta_k$ for $k = 1, \ldots, 21$

ing p-values for each variable as depicted in Figure 3. The corresponding cointegration tests for weighted and nominal models are shown in Figures 4 and 5, respectively. In addition, Figure 6 shows transitions of p-values for structural breaking Chow tests for each model. According to the Chow test, the sign of the structural break appears at $k = 15$ to be more clear at $k = 16$.

Using the result of Chow test and concerning the sample size, altcoins are divided into two groups around $i = 15$. The results for the separated regressions are shown in Table 8. The cointegration test for $i \in \Theta_{15}$ is as shown in Figures 4 and 5, and we can see that there is no cointegration problem. The cointegration test for $i \neq \Theta_{15}$ can be done only when there is no lag due to insufficient time series observations for some altcoins. Yet, the test statistic for the cointegration test (ADF and PP become identical to each other in such a case) is -17.46 that is sufficiently large to reject the existence of cointegration.

The corresponding identification tests for weighted and nominal models are provided by Table 9. The average group size (average of T) for the upper group is about 22.62 and for the lower group is about 9.33. This implies that the condition for Proposition 1 is less likely satisfied by the minor altcoins. This implies that the weighted model for $i \neq \Theta_{15}$ contains lots of noises to fail rejecting the null hypothesis for the underidentification test in Table 9. Thus the nominal model is picked up for separated regressions for further considerations.

4 Inferences

As shown by Table 1, there are some correlations between EUR and JPY and between CNY and BTC. Especially, when we want to talk about insignificance, such correlations must be consulted carefully. Table 10 then looks at each

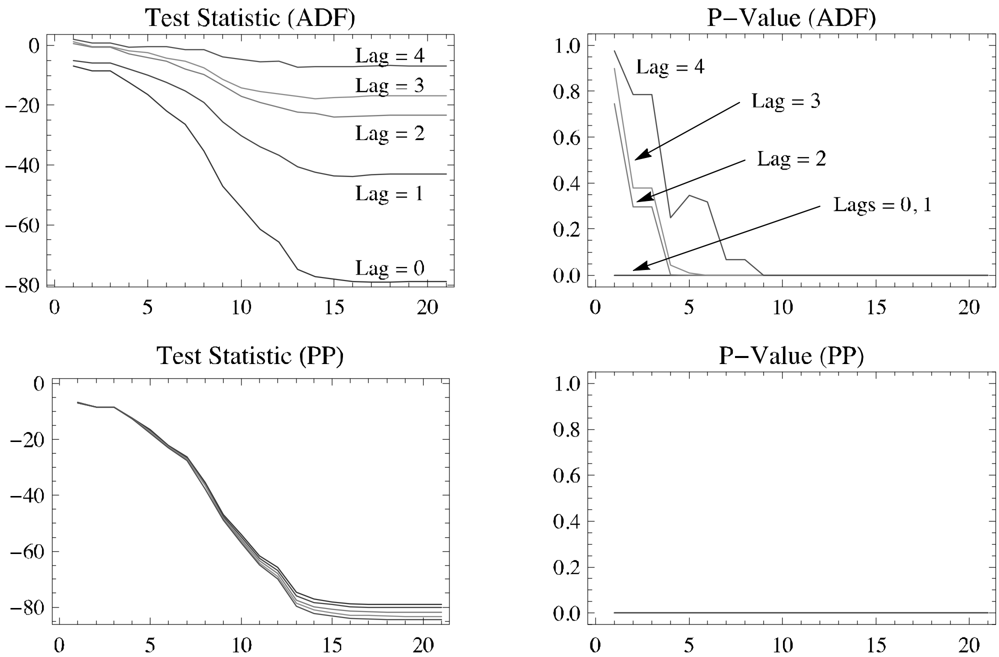

Figure 4: Cointegration tests for weighted model

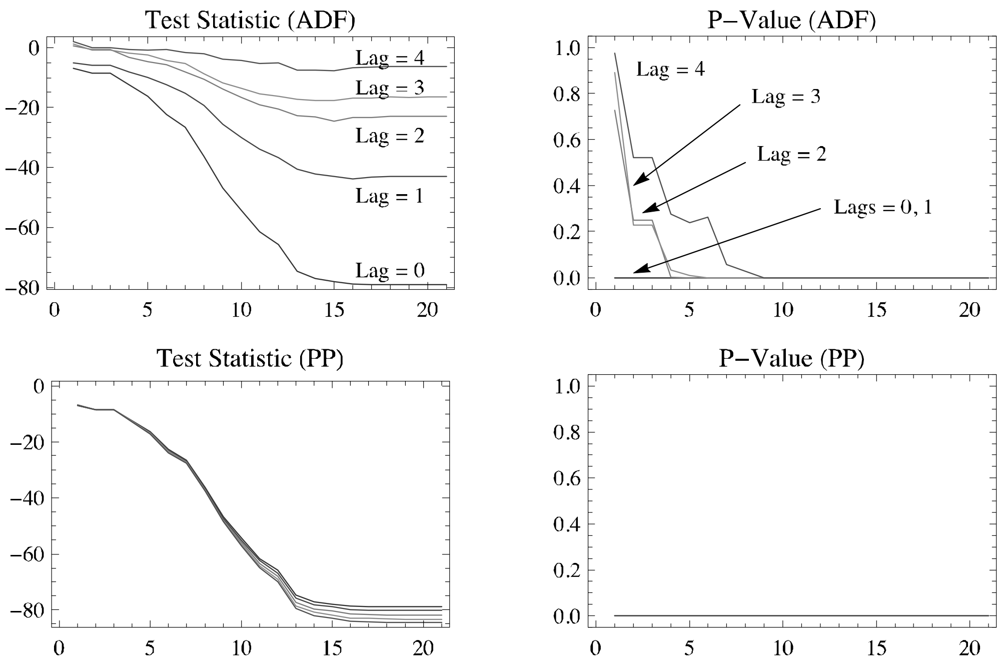

Figure 5: Cointegration tests for nominal model

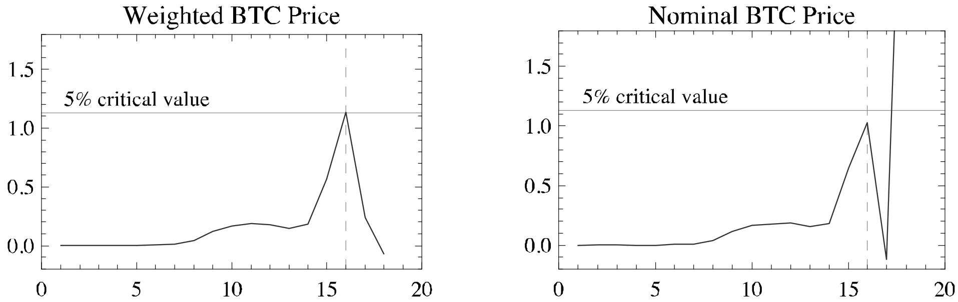

Figure 6: Structural break tests

Table 8: Separeted regressions results (robust s.e.)

	Major ALTs: $i \in \Theta_{15}$		**Minor ALTs:** $i \notin \Theta_{15}$	
	weighted	*nominal*	*weighted*	*nominal*
β_{ALT}	0.9007^{**}	0.9024^{**}	0.8110^{**}	0.8061^{**}
(*s.e.*)	(0.0167)	(0.0168)	(0.0196)	(0.0845)
β_{BTC}	-0.8701	-0.0255	5.8E+5	$-0.6152^{\dagger}$
(*s.e.*)	(2.2395)	(0.0376)	(4.5E+5)	(0.3632)
β_{EUR}	0.3247	$0.4120^{\dagger}$	1.9207	1.2388
(*s.e.*)	(0.2173)	(0.2480)	(2.7353)	(2.8594)
β_{JPY}	0.3750	0.3173	-2.4011	-2.0279
(*s.e.*)	(0.3980)	(0.4048)	(4.5141)	(4.5479)
β_{CNY}	-0.8683^{**}	-1.1411^{*}	4.6202	-6.9239
(*s.e.*)	(0.3182)	(0.5249)	(4.8242)	(5.1989)
R^2	0.6042	0.6044	0.4035	0.4050
obs.	6,898	6,898	504	504
altcoins	305	305	54	54

Table 9: Identifications and endogeneity tests for separated 2SLS

		weighted		**nominal**	
		$i \in \Theta_{15}$	$i \notin \Theta_{15}$	$i \in \Theta_{15}$	$i \notin \Theta_{15}$
underidentification test	test statistic	506.623	0.000	476.109	39.509
(H_0: model is underidentified)	p-value	0.0000	1.0000	0.0000	0.0000
weak identification test	test statistic	1444.901	0.000	1226.563	99.213
(H_0: model is weakly identified)	p-value	—	—	—	—
endogeneity test	test statistic	102.382	11.277	46.397	11.141
(H_0: endogenous regressors are treated as exogenous)	p-value	0.0000	0.0036	0.0000	0.0038

Table 10: Joint significance tests

		weighted	nominal	
		Pooled	$i \in \Theta_{15}$	$i \notin \Theta_{15}$
joint significance of EUR and JPY	test statistic	14.17	11.54	0.21
(H_0: $\beta_{EUR} = \beta_{JPY} = 0$)	p-value	0.0008	0.0031	0.8990
joint significance of CNY and BTC	test statistic	6.96	7.85	3.00
(H_0: $\beta_{CNY} = \beta_{BTC} = 0$)	p-value	0.0308	0.0197	0.2232

Table 11: Summary of results

	Bitcoin	weighted	nominal	
	$i = 1$	$i \in \Theta$	$i \in \Theta_{15}$	$i \notin \Theta_{15}$
Bitcoin	—	weak	weak	(+)
Euro	(+)	(+)	(+)	insignificant
Japanese Yen	weak	weak	weak	insignificant
Chinese Yuan	(−)	(−)	(−)	weak

joint significance. According to the table, we cannot say insignificance of JPY and BTC in the pooled model and the separated model for major altcoins ($i \in \Theta_{15}$); whence, we should say impacts of JPY and BTC are *weaker* than EUR and CNY, respectively, instead of saying *insignificant*. However, we are able to say it EUR and JPY are jointly insignificant in the separated model for minor altcoins ($i \notin \Theta_{15}$). The joint significance of CNY and BTC is ambiguous because the p-value for the joint significance test is 0.2232 while the p-value for the independent significance of BTC is at 10% level, as shown in Table 8. With these notions, we derive inferences of statistical results in the following paragraphs.

Based on statistical arguments provided in Section 3, adopted results for considerations are summarized in Table 11. In the weighted model, each altcoin is treated as equal in terms of relative capitalization as Bitcoin. With this notion, in accordance with results for Bitcoin, weighted model, and nominal model for major altcoins ($i \in \Theta_{15}$), each non-minor cryptocurrency (inclusive of Bitcoin and other altcoins) has a positive correlation with Euro while it is negative with Chinese Yuan, so that, Euro seems a complement of major altcoins and CNY a substitute for them. Impacts of JPY and BTC are much weaker than EUR and CNY, respectively. Similar results are also seen in the regression for Bitcoin price. In turn, if we focus on minor altcoins ($i \notin \Theta_{15}$), there are no significances of EUR, JPY, and CNY while the significance of BTC gets rather stronger.

Statistical results for major and minor altcoins also suggest that Bitcoin has direct effects on minor altcoin prices, but its effect becomes rather indirect on major ones. Minor coins could be made for tunnels to obtain Bitcoin, as mining Bitcoin is getting harder and harder, and then the effect of Bitcoin price on minor altcoin prices could be direct. Major altcoins are getting more like Bitcoin that are able to behave as a currency within foreign exchange markets, so that, such major altcoin prices are more directly affected by staple-currency exchange rates than Bitcoin price. Including Bitcoin, major cryptocurrencies seem to behave axis currencies such as EUR to complement them and to substitute for emerging currencies such as CNY.

5 Conclusion

This study has investigated a time-series data of altcoin prices in terms of Bitcoin and some major foreign currencies such as Euro, Japanese Yen, and Chinese Yuan. In the separated regression for major altcoins, we find that major altcoins are complements of Euro and substitutes for Chinese Yuan. In addition, it is also shown that impacts of Bitcoin and Japanese Yen on major altcoins are weak. Equivalent results are seen in the pooled regression that uses a weight based on respective relative market capitalizations in terms of the Bitcoin capitalization, as well as the regression for Bitcoin itself. Since the weight treats minor altcoins as if major altcoins in terms of Bitcoin, the results of the pooled regression reinforce the results of the separated regressions for major altcoins.

In the separated regression for minor altcoins, we find that major foreign currencies lose their impacts on price formations of minor altcoins and Bitcoin obtains some power. In the minor altcoin market, Bitcoin becomes a substitute for such minor ones. Major cryptocurrencies seem to complement axis currencies such as Euro and substitute for emerging currencies such as Chinese Yuan. Yet, minor altcoins are still substitutes for Bitcoin and are probably tunnels to obtain Bitcoin that gets harder to get through mining activities.

For further studies, concerning the recent rise of Etherium, we should try to figure out how Etherium is characterized in the altcoin market and how it is correlated with Bitcoin. In addition, we should investigate if equivalent results are obtained by equivalent time-series data of different period and length.

Appendix

A Proof of Proposition 1

Let $dp_{j,s} \equiv 0$ for all $j \neq i$ and $s \neq t$ and $dp_{1,s} \equiv 0$ for all $s \neq t-1$. Totally differentiating the first equation in the equation system (1) provides

$$dp_{i,t} = \beta_{BTC}\omega_i dp_{1,t-1} + \beta_{BTC} p_{1,t-1} d\omega_i, \tag{8}$$

where $dp_{i,t} = dP_{i,t}/P_{i,t}$ and $dp_{1,t-1} = dP_{1,t-1}/P_{1,t-1}$. The partial elasticity of Altcoin i, $e_{i,t}$, is then computed as

$$\frac{dP_{i,t}}{dP_{1,t-1}}\frac{P_{1,t-1}}{P_{i,t}} \equiv e_{i,t} = \omega_i\beta_{BTC} + \beta_{BTCi} p_{1,t-1}\left(P_{1,t-1}\cdot\frac{d\omega_i}{dP_{1,t-1}}\right), \tag{9}$$

where the expression within the braces is computed and arranged as

$$P_{1,t-1}\cdot\frac{d\omega_i}{dP_{1,t-1}} = P_{1,t-1}\cdot\frac{\partial\omega_i}{\partial P_{1,t-1}} + P_{i,t}\cdot\frac{\partial\omega_i}{\partial P_{i,t}}\left(\frac{dP_{i,t}}{dP_{1,t-1}}\frac{P_{1,t-1}}{P_{i,t}}\right). \tag{10}$$

Respective derivatives of ω_i in terms of $P_{1,t-1}$ and $P_{i,t}$ are computed from (2) to get

$$\frac{\partial\omega_i}{\partial P_{1,t-1}} = \frac{1}{T}\frac{S_{1,t-1}C_{i,t-1}}{C_{1,t-1}^2} \quad \text{and} \quad \frac{\partial\omega_i}{\partial P_{i,t}} = \frac{1}{T}\frac{S_{i,t}}{C_{1,t}}, \tag{11}$$

which imply that

$$P_{1,t-1}\cdot\frac{\partial\omega_i}{\partial P_{1,t-1}} = \frac{1}{T}\frac{C_{i,t-1}}{C_{1,t-1}} \simeq 0 \quad \text{and} \quad P_{i,t}\cdot\frac{\partial\omega_i}{\partial P_{i,t}} = \frac{1}{T}\frac{C_{i,t}}{C_{1,t}} \simeq 0, \tag{12}$$

where approximations follow from a sufficiently large T and the fact that Bitcoin has a huge market capitalization value. Thence $P_{1,t-1}\cdot d\omega_i/dP_{1,t-1} \simeq 0$ is held and the partial elasticity of ALT i is approximately computed as $e_i = \omega_i\beta_{BTC}$ as time-independent.

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