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MCIS 2016 Proceedings

Mediterranean Conference on Information Systems (MCIS)

2016

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ALTCOINS AS ALTERNATIVES FOR WHAT?

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1 Introduction

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. This paper uses a time-series data for altcoins to see correlations among these altcoins and Bitcoin, Euro, Japanese Yen, and Chinese Yuan. The dataset is a dynamic panel data (unbalanced) gathered from coinmarketcap.com that provides real-time market data for more than 600 cryptocurrencies.

2 Statistical Strategy

2.1 Dataset

The dataset is a dynamic panel data (unbalanced) gathered from an online content. 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. Effectively, in actual estimations, 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.

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.

2.2 The Model

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 a structure of pricing system as simultaneous equations model assuming that daily rates conform to a Poisson process.

Let $J = \{EUR, JPY, CNY\}$ be the set of chosen exchange rates, $p_{i,t} = \ln P_{i,t}$ 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 $\varphi_{i,t}$ be the fixed effect. Considering efficiency of estimation, the structural equation system is provided as a nested model:

$$\begin{cases} p_{i,t} = \beta_0 + \beta_{ALT} p_{i,t-1} + \beta_{BTC} \omega_i p_{1,t-1} + \sum_{j \in J} \beta_j p_{j,t-1} + \phi_i + \varepsilon_{i,t} \\ p_{i,t-1} = \alpha_i + \alpha_i p_{i,t-2} + \alpha_{BTC} \omega_i p_{1,t-2} + \sum_{j \in J} \beta_j p_{j,t-1} + \eta_{i,t-1} \\ \omega_i p_{1,t-1} = \gamma_i + \gamma_i p_{i,t-2} + \gamma_{BTC} \omega_i p_{1,t-2} + \sum_{j \in J} \gamma_i p_{j,t-1} + \mu_{i,t} \end{cases}, \tag{2.1}$$

where ω_i in the regression model is

$$\omega_i = \begin{cases} \frac{1}{T} \sum_{t=1}^{T} \frac{C_{i,t}}{C_{1,t}} & \text{(if weighted)} \\ 1 & \text{(if not weighted)} \end{cases}. \tag{2.2}$$

This parameter adjusts the nominal price for smaller altcoins compared with BTC when ω_i is weighted, so that it is useful especially in a pooled regression. The weight ω_i will bring additional endogenous structure that will be controlled by the third equation in (2.1).

2.3 Procedures

The estimations follow steps as described in Table 1. The weighted model is applied for a pooled regression and the non-weighted model for a separated regression. Before estimations, we look at unit-root tests (Phillips-Perron and Augmented Dickey-Fuller tests) to see if the dataset has serial correlations within each time-series variable. After estimations, we look at cointegration tests (Phillips-Perron and Augmented Dickey-Fuller tests) to see if there are serial correlations among errors. In addition, we also examine if there is hetergoskedasticity (Breusch-Pagan test). The two tests guarantees rigorousness of significance of estimates. Then, we further look at identification tests to see if simultaneous equation models are adequate. In the non-weighted model, we also run structural breaking tests (Chow tests) for each cut-off levels based on relative market capitalization ω_i to find an appropriate structural breaking point.

Weighted Model	**Non Weighted Model**
Step 1. Unit-root test	Step 1. Unit-root test
Step 2. 2SLS estimation	Step 2. 2SLS estimation *for each cut-off level*
Step 3. Cointegration test	Step 3. Cointegration test
Step 4. Heteroskedasticity test	Step 4. Heteroskedasticity test
Step 5. Identification tests	Step 5. *Structural breaking test*
Step 6. Conclusion	Step 6. Identification tests
	Step 7. Conclusion

Table 1 Procedures of estimations for each model (weighted and non weighted).

3 Main Results

3.1 Bitcoin

Prior to looking at results for altcoins, we check the regression result for BTC (i = 1):

$$p_{1,t} = -13.19 + 0.6267^{**} p_{1,t-1} + 1.6684^{\dagger} p_{EUR,t-1} - 1.1912 p_{JPY,t-1} - 5.1430^{**} p_{CNY,t-1} + \varepsilon_{1,t}. \tag{3.1}$$

The sample size of this regression is 41 and R^2 is 0.8535. We cannot find significant heteroskedasticity and serial correlations among errors.

3.2 Altcoins

3.2.1 Pooled Regression

The result for the pooled regression for altcoins is provided by

$$p_{i,t} = \beta_0 + 0.8848^{**} p_{i,t-1} - 0.7442\beta_{1,t-1} + 0.5226^{*} p_{EUR,t-1} + 0.2053 p_{JPY,t-1} - 0.8634^{**} p_{CNY,t-1} + \phi_i + \varepsilon_{i,t}. \tag{3.2}$$

The sample size of this regression is 7,402 with 359 and R^2 is 0.5622. We cannot find significant serial correlations among errors. However, we cannot reject the existence of heteroskedasticity, so robust errors are applied to see significance of estimates.

3.2.2 Separated Regression

The structural breaking test suggests that the signal of the structural break appears when ω_i reaches 1.22×10^{-6} and the signal becomes significant at 10% level when ω_i reaches 6.10×10^{-7}. In order to group coins for separated regressions, we apply $\omega_i = 1.22\times10^{-6}$ to keep sample size of minor coins. We then find the following two results.

The result for the separated regression for altcoins for major coins is provided by

$$p_{i,t} = \beta_0 + 0.9024^{**} p_{i,t-1} - 0.0255\beta_{1,t-1} + 0.4120^{\dagger} p_{EUR,t-1} + 0.3173 p_{JPY,t-1} - 1.1411^{**} p_{CNY,t-1} + \phi_i + \varepsilon_{i,t}. \tag{3.3}$$

The sample size of this regression is 6,898 with 305 and R^2 is 0.6044. Similarly, the result for the separated regression for altcoins for minor coins is provided by

$$p_{i,t} = \beta_0 + 0.8061^{**} p_{i,t-1} - 0.6152^{\dagger}\beta_{1,t-1} + 1.2388 p_{EUR,t-1} - 2.0179 p_{JPY,t-1} - 6.9239 p_{CNY,t-1} + \phi_i + \varepsilon_{i,t}. \tag{3.4}$$

The sample size of this regression is 504 with 54 and R^2 is 0.4050. We cannot find significant serial correlations among errors in the two regressions. However, we cannot reject the existence of heteroskedasticity in the two regressions, so robust errors are applied to see significance of estimates.

4 Concluding Remarks

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. The results are summarized in Table 2.

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. However, Bitcoin obtains some power in the minor altcoin market. In the minor altcoin market, Bitcoin becomes a substitute for such minor ones.

	Bitcoin	Euro	Japanese Yen	Chinese Yuan
Bitcoin	N.A.	(+)	weak	(–)
Pooled (Weighted)	weak	(+)	weak	(–)
Separated (Major)	weak	(+)	weak	(–)
Separated (Minor)	(+)	insignificant	insignificant	weak

Table 2 Summary of the results