

Enhancing Predicting Performance in Cryptocurrency Market Using Interdependency of Price and Sentiment Values

Ying Lu

Faculty of Business and Economics
The University of Hong Kong
alvinlu@hku.hk

Michael Chau

Faculty of Business and Economics
The University of Hong Kong
mchau@business.hku.hk

Although herding behavior and co-movements have been confirmed in the digital currency market, the predictivity of interdependency between cryptocurrencies has not been testified yet, let alone the practical predicting model to utilize all these features accordingly. This paper intends to testify the predictivity of price independency and sentiment values. After conducting an ARMA test, more price interdependency has been confirmed, and sentiment values from social media have been proved helpful in predicting as well. Empirical study shows the significance of these factors as input for predicting.

Keywords—Cryptocurrency, Interdependency, Price, Sentiment, Predictivity

I. INTRODUCTION

The interdependency relations among different companies have been confirmed as a useful indicator to enhance predicting performance in the traditional stock market[1]. However, in the digital currency market, the inter-coin relations have not been testified as effective as the one from the stock market. Although herding behavior has been detected between the leading digital currencies[2] and co-movements between bitcoin and Ethereum are confirmed in the various period by [3], no research has illustrated predictivity of interdependency by different currencies, although the correlations between each coin are useful tools for investors to apply in their portfolio. Hence, we firstly intend to capture the interdependency between leading currencies in this paper and try to illustrate the degree to which each of the coins is capable of predicting the others.

On the other side, texts have long been confirmed its assistance in enhancing prediction in traditional stock markets. Similarly, some researchers have studied the capability of sentiment values to predict price values in the Bitcoin case[4]. Although Bitcoin, one of the primarily leading coins, will the sentiment values of Bitcoin in social media be the most dominating reflection of price tendency in the market? Will the online comments of other coins also play prophetic roles and to what extent do they succeed in predicting? In this paper, we shall explore more about these

questions. As a summary, we mainly focus on the following research points in this paper:

- To what extent will the price values of one coin reflect the tendency of the price values of other coins.
- Will the price interdependency facilitate price prediction in crypto markets.
- To what extent the sentiment values of one coin can be helpful in predicting the price tendency of other coins.

II. LITERATURE REVIEW

In the field of cryptocurrency research, interdependency of price values is one of the hot topics. Herding effects have been proved between different digital currencies [2], but only when uncertainty increases. Likewise, co-movement between Bitcoin and Ethereum was also detected[3]. However, other leading coins, such as Ripple, have not been considered yet.

As for the interdependency of price values between leading coins, some research conducted works focusing on spillover effects among leading cryptocurrencies[5], which supports the existence of interdependence. There had been some research which intends to make improvements of price prediction in this market, one of them combined GARCH and SVR in order to get both price fluctuation features and to make a prediction[6]. Another one proposed a non-linear perspective to make prediction[7]. However, unlike the research in the field of the stock market, works in crypto markets did not testify whether price co-relation plays a profiting role in prediction. Hence, this serves as the second research points in this paper.

Sentiment-related research of digital coins is rare. Previous research validates the different roles played by both the active minority and the silent majority of social media, and also illustrated the predictivity of sentiment in the digital currency market[4]. In this paper, we engage to explore about predictivity of various currencies, rather than Bitcoin alone.

III. EMPIRICAL ANALYSIS

A. Data Description

We have collected data from a leading cryptocurrency transaction platform. In the current experiment, we only use price data at the timestamp from 2018-02-15 to 2018-05-05 and the corresponding textual resources. All sentiment values are extracted from texts crawled from Reddit. Because of limits of time, we have just collected texts of Bitcoin, Ethereum and Ripple. The three textual dataset contains 5562, 1530 and 410 pieces of texts.

B. Econometric Analysis

Interdependency of price values

In order to detect whether there is interdependency among cryptocurrencies, a correlation test between TOP 10 coins in the market has been practiced. These coins have been selected by using market capitalization as an indicator.

Table 1 shows a correlation matrix, containing correlation values between each pair of prices from two coins. We choose three leading coins, namely Bitcoin, Ethereum and Ripple, to do the future analysis. As shown in Figure 1(a), for bitcoin, Ethereum has a most significant correlation, whereby Ripple also indicates a correlation with the value of 0.92. However, not all leading coins show a strong correlation with bitcoin, and some change quite differently. As for Ethereum, only Ripple shows a strong correlation with Ethereum, while bitcoin express less than 0.95. In the case of Ripple, only Ethereum correlates with a value of 0.96, showing a close connection, however, bitcoin does not fit with it well. The results roughly confirm the conclusion that there are herding effects along various coins in the market [2], but the significance of each pair varies. Also, the co-movement between Bitcoin and Ethereum[3] have been testified, but in some cases, other coin co-movements with bitcoin or Ethereum as well. As a

conclusion, interdependency could be used as an indicator when selecting predictors for a cryptocurrency.

Predictivity Evaluation

In order to testify the predictivity of both price and sentiment. After experiments, we choose ARMA(1,1) and NLS to make regression. For the price value of one coin at the timestamp of T, the regression is :

$$P_T = \sum_{i=1}^3 C_i P_{T-1}^i + \sum_{i=1}^3 w_i S_{T-1}^i + C + \varepsilon \quad (1)$$

Where P_{T-1}^i stands for the price value of the i th coin at the timestamp of T-1, S_{T-1}^i for the sentiment value of the i th coin at the timestamp of T-1, C for constant and ε for the residuals.

Because of limits of raw texts resources, we only choose Bitcoin, Ethereum and Ripple as prediction targets. Specifically, we estimate whether derivation of price or sentiment values from other coins can perform well in predicting price derivation on the next day. Table 2 presents results of ARMA estimation. For bitcoin, derivation of price, unluckily, can only be predicted effectively by derivation of Ethereum. Sentiment change from Ethereum and Ripple cannot be helpful here. However, In the case of Ripple, sentiment value from Ripple itself contributes a coefficient with a probability of 0.02.

Meanwhile, derivation of Ethereum also presents a more significant effect in predicting. Like Ripple, Ethereum can also be better predicted with the assistance of sentient values from Bitcoin (with a probability value of 0.01) and Ripple (with a probability value of 0.03), while derivation of prices from the other two coins contributes more in prediction. From these rudimental data, it is reasonable to conclude that sentient value also benefits the price prediction in the crypto market.

TABLE 1. CORRELATION MATRIX BETWEEN TOP 10 CRYPTOCURRENCIES

	BTC	BTC_CASH	CARDANO	EOS	ETHER	LITECOIN	MONERO	RPP	STELLAR	TRON
BTC	1.00000									
BTC_CASH	0.84323	1.00000								
CARDANO	0.81058	0.90599	1.00000							
EOS	0.30863	0.67060	0.68718	1.00000						
ETHER	0.96072	0.86393	0.86270	0.33014	1.00000					
LITECOIN	0.93026	0.73176	0.70599	0.05843	0.94465	1.00000				
MONERO	0.95144	0.78826	0.75428	0.26625	0.91683	0.87338	1.00000			
RPP	0.92816	0.90595	0.91889	0.43430	0.96401	0.88206	0.90563	1.00000		
STELLAR	0.76101	0.91262	0.97312	0.75437	0.80709	0.62159	0.73927	0.89612	1.00000	
TRON	0.31657	0.66923	0.64566	0.96644	0.31389	0.05922	0.26703	0.40317	0.71689	1.00000

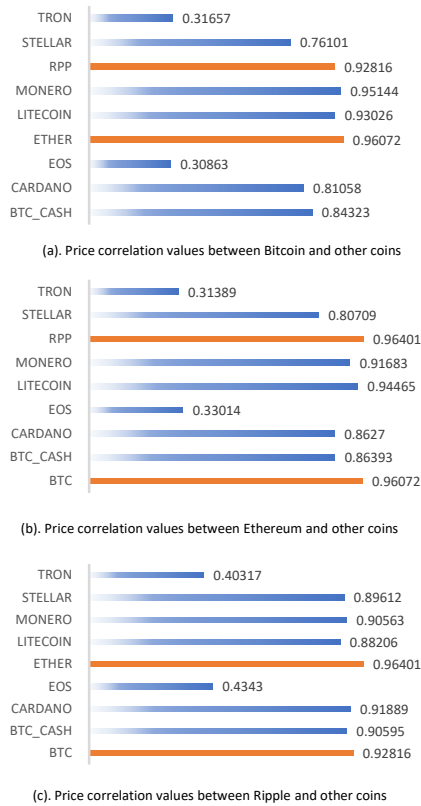


FIGURE 2. THE OVERALL FRAMEWORK OF PREDICTION MODELS USING BOTH INTERDEPENDENCIES OF PRICE VALUES AND SENTIMENTS

TABLE 2. ARMA ESTIMATION RESULTS USING BITCOIN, ETHEREUM AND RIPPLE DATA

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Dependent Variable: D_BTC				
D_ETHER	8.108088	1.613064	5.026512	0.0000
D_RPP	2051.071	1156.917	1.772876	0.0804
T_BTC	96.37403	161.3254	0.597389	0.5521
T_ETHER	22.39628	123.1486	0.181864	0.8562
T_RPP	-1.615909	62.43026	-0.025883	0.9794
C	-45.41550	79.32415	-0.572530	0.5687
Dependent Variable: D_RPP				
T_BTC	0.022419	0.015803	1.418655	0.1603
T_ETHER	-0.019857	0.011978	-1.657763	0.1017
T_RPP	-0.013884	0.005967	-2.326862	0.0228
D_BTC	2.01E-05	1.14E-05	1.772876	0.0804
D_ETHER	0.000968	0.000147	6.598227	0.0000
C	0.007109	0.007831	0.907762	0.3670
Dependent Variable: D_ETHER				
T_BTC	-24.42852	9.701113	-2.518115	0.0140
T_ETHER	5.626332	7.675070	0.733066	0.4659
T_RPP	8.210203	3.784209	2.169595	0.0333
D_BTC	0.031711	0.006309	5.026512	0.0000
D_RPP	385.8875	58.48350	6.598227	0.0000
C	3.953226	4.950358	0.798574	0.4271

IV. CONCLUSIONS AND FUTURE WORKS

From the results shown in the last section, some conclusions can be roughly confirmed:

- There is significant correlation between price values of different leading coins, not only between Bitcoin and Ethereum. Among all the ten leading currencies, Bitcoin, Ethereum and Ripple have the most strong predictivity.
- The sentiment values from Ripple perform best in predicting price values of both Ripple and Ethereum. However, sentiment value did not predict well in Bitcoin case.

Limited by time and available texts, this paper has not been finalized. Future works include more experiments of testing the predictivity of sentiments from more coins, more inclusive data collection and further testification about how the interdependency of price and how the predictivity of both price and sentiment vary by time.

V. ACKNOWLEDGMENTS

The authors would show sincere thanks to partners from Santiment.net for their kind supports: Ms. Maria, Ms. Serena, and Mr. Valentin.

REFERENCES

- [1]. K. Chen, P. Luo, D. Xu, and H. Wang, "The dynamic predictive power of company comparative networks for stock sector performance," *Information & Management*, vol. 53, pp. 1006-1019, 2016.
- [2]. E. Bouri, R. Gupta, and D. Roubaud, "Herding behavior in cryptocurrencies," *Finance Research Letters*, vol. pp. 2018.
- [3]. P. Katsiampa, "Volatility co-movement between Bitcoin and Ether," *Finance Research Letters*, vol. pp. 2018.
- [4]. F. Mai, Z. Shan, Q. Bai, X. Wang, and R. H. L. Chiang, "How Does Social Media Impact Bitcoin Value? A Test of the Silent Majority Hypothesis," *Journal of Management Information Systems*, vol. 35, pp. 19-52, 2018.
- [5]. D. Koutmos, "Return and volatility spillovers among cryptocurrencies," *Economics Letters*, vol. 173, pp. 122-127, 2018.
- [6]. Y. Peng, P. H. M. Albuquerque, J. M. Camboim de Sá, A. J. A. Padula, and M. R. Montenegro, "The best of two worlds: Forecasting high frequency volatility for cryptocurrencies and traditional currencies with Support Vector Regression," *Expert Systems with Applications*, vol. 97, pp. 177-192, 2018.
- [7]. W. Kristjanpoller and M. C. Minutolo, "A hybrid volatility forecasting framework integrating GARCH, artificial neural network, technical analysis and principal components analysis," *Expert Systems with Applications*, vol. 109, pp. 1-11, 2018.