Chapter 6
Herding Behaviour in Cryptocurrency Market: CSSD and CSAD Analysis

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Abstract Cryptocurrencies get substantial attention of investors as recently created innovations. This chapter focuses on herding behaviour in the cryptocurrency market, considering CSSD and CSAD approaches for cryptocurrencies in the CCI 30 Index. The analysis focuses on the cryptocurrency index and cryptocurrencies, which have existed since the arbitrarily set starting date of the index. In addition to the CCI 30 Index, as a proxy for market, Bitcoin, Litecoin, Stellar, Monero, Dogecoin and Dash are used for empirical analysis. To the best of the author's knowledge, the CCI 30 Index is used for the first time as a proxy for market return. Despite the growing literature on cryptocurrencies, there is still a gap in herding behaviour in the cryptocurrency market. Results indicate no evidence of herding behaviour in the cryptocurrency market in both CSSD and CSAD approaches. The findings of both approaches are in line with the findings of the previous literature regarding the herding behaviour in cryptocurrencies such as Bouri et al. (Financ Res Lett 29:216–221, 2018) and Vidal-Tomás et al. (Financ Res Lett doi: 10.1016/j.frl.2018.09.008, 2018).

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6.1 Introduction

Technological developments affect all sides of the economy. Those improvements and explorations reshape the financial system as well. An article published in 2008 by Nakamoto also mentions these types of improvements. The author discussed the possibility of an electronic payment system between two willing parties to transact directly without a trusted third party. This system is called a blockchain and the medium of exchange is called crypto currency.

Bitcoin was the first cryptocurrency generated in that system. Today, there are almost 2000 cryptocurrencies (CoinMarketCap). Their total market value is $104.542.780.889 as of February 4, 2019. Bitcoin exists as the first mover advantage and has 58% market share according to the total market capitalization. XRP and Etherium are the closest followers with 12 and 11% market share respectively.

This chapter intends to identify and analyze the herding behaviour in the cryptocurrency market, taking CCI 30 Index and cryptocurrencies of that index into account for the January 1, 2015 and December 31, 2018 historical periods. The study contributes to the cryptocurrency market literature by considering herding behaviour of a larger sample and by using the first generated cryptocurrency index with the longest time period.

This paper is organized as follows. Section 6.2 describes the theoretical framework and terminology used throughout this paper as well as the previous studies. Section 6.3 describes data and research methodology used for empirical analysis. Sections 6.4 indicates the findings of the analysis and finally Sect. 6.5 provides the conclusion of this paper.

6.2 Theoretical Framework

Herding is defined as the result of a clear intent by investors to mimic other investors' behaviours (Bikhchandani & Sharma, 2000). For imitating another, an investor must be aware of and be affected by other investors' positions. For instance, the investor would invest without having information about other investors' actions, but does not invest when learning that other investors' don't invest. Thus, investors may herd on a wrong investment decision, if they are influenced by other investors' decisions.

One of the main reasons of following the others rather than using their own beliefs is the uncertainty. Owing to evolutionary reasons, people tend to imitate others in the case of uncertainty according to the socioeconomic theory. Parker and Prechter (2005) state that, people unconsciously follow and imitate others, which is known as herd behavior in finance literature. By imitating others, traders think that others know better than they do, so they keep imitating.

Emerging markets differ from developed markets in terms of depth of financial markets and variety of financial instruments, as well as the differences in regulations.

Kremer (2010) states that in developing countries uncertainty is higher than in developed ones, due to less developed regulatory frameworks. Namely, due to the uncertainty, traders may follow others with a hope of having higher returns.

Herding behaviour has taken place in financial markets since the first financial crisis known as Tulipmania in the seventeenth century followed by the 2008 subprime mortgage crisis and the dot-com bubble of the 2000s (Bouri, Gupta, & Roubaud, 2018).

Herd behaviour is common among all types of investors (institutional or individual), and generally causes high market volatility and instability in the markets (Spyrou, 2013). Causes of herding include inferring information from previous investors' actions, reacting to newly arrived important information, protecting reputation, and irrationality of the investors.

Avery and Zemsky (1998) stated that herding caused by informational cascade is not possible in case of plain information structures and price mechanisms, however herd may exist if complicated information structures, and uncertainty in asset value and information are assumed. Technology itself and also the ambiguity related to the blockchain system and crypto currencies are the rationality behind searching herding behaviour in the cryptocurrency market. Intrinsically, the system in and of itself causes participants to perceive as if there is uncertainty. From causes of herding behaviour perspective, the complicated structure of the blockchain system and differences among average cryptocurrency traders' information levels may explain the possibility of the existence of herding in the cryptocurrency market.

Cryptocurrencies are financial instruments currently introduced to the financial markets. For this reason, this gap has attracted the attention of researchers. The recent studies mostly focus on market efficiency and price dynamics (Corbet, Lucey, & Yarovaya, 2018a).

Considering the extreme speculative nature of cryptocurrencies, Bitcoin being the largest currency in cryptocurrency market, makes the cryptocurrency market volatile (Baur, Hong, & Lee, 2018). This extreme volatility in the market might result in herding behaviour. For this reason, traders of cryptocurrencies are not as sensitive as the traders in the financial markets (Bouri et al., 2018).

Sapuric and Kokkinaki (2014) investigates the relationship and volatility between Bitcoin and six major currencies whereas Cheung, Roca, and Su (2015) empirically analyzes the bubbles in the Bitcoin market, using the Phillips et al. methodology. With the help of this method, the authors find a number of short-lived bubbles, and three large bubbles lasting from 66 to 106 days. The occurrence of these bubbles is coincided with some major events that take place in the Bitcoin market, the most significant of these being the demise of the Mt. Gox exchange.

Zhang, Wang, Li, and Shen (2018) focuses on statistical characteristics of the cryptocurrencies return based on the existence of heavy tails, volatility clustering, leverage effects and the presence of a power-law correlation between price and volume. Chuen and Deng (2017) implemented some statistical methods such as ARIMA, GARCH and EGARCH modelling to the CRIX indices family in order to find out the volatility clustering phenomenon and the presence of fat tails.

Urquhart (2017) investigates the efficiency of Bitcoin returns from August 2010 to July 2016 by implementing various tests for randomness such as Ljung-Box, Runs, Bartels, Automatic variance test, BDS, R/S Hurst tests. The study finds that returns are significantly inefficient over the analyzed period. Then, the period is divided into two equal sub-samples. The tests reveal efficiency of returns in the sub-samples, suggesting that Bitcoin may be moving towards becoming more efficient.

Nadarajah and Chu (2017) test the efficiency in Bitcoin in USD from August 1, 2010 and July 31, 2016. Data is analyzed in three periods: the full period from the first of August 2010 to 31st of July 2016; the subsample period from the first of August 2010 to 31st of July 2013 and the subsample period from the first of August 2013 to 31st of July 2016. Eight different tests are implemented on the data to find out the efficiency of the Bitcoin market.

Kristoufek (2015) researches the main drivers of the price and price formation of Bitcoin by using utilized wavelets methodology. Although Bitcoin is assumed as a speculative financial instrument, the findings reveal that usage in trade, money supply and price level are the factors that play a role in Bitcoin price in the long term.

In the financial markets, the traders can either behave rationally or irrationally. When the traders behave rationally, assumptions of asset pricing models are proved. On contrary, if the investors behave irrationally and imitate others rather than using their own beliefs based on the information, herd behaviour occurs. The existence of herd behaviour in the financial markets means that the assumptions of Efficient Market Hypothesis are disagreed upon (Caparrelli, D'Arcangelis, & Cassuto, 2004; Fama, 1965; Lao & Singh, 2011).

Some papers have analyzed the relationship between digital currencies in the cryptocurrency market. For instance, Ciaian and Rajcaniova (2018) examines the interdependencies between Bitcoin and 16 digital currencies from 2013 to 2016. Findings show that Bitcoin and altcoin markets are interdependent. In the short term, the Bitcoin-altcoin price relationship is significantly stronger than in the long run.

Gandal and Halaburda (2016) investigate the daily price (i.e., exchange rate) data in the analysis from 2 May 2013 to 1 July 2014 between Bitcoin and 7 altcoins. The study examines how the prices of cryptocurrencies change in time by applying a reinforcement effect and a substitution effect. Findings show positive correlations between the cryptocurrencies.

Osterrieder and Lorenz (2017) analyze an extreme value analysis of the returns of Bitcoin. Study focuses on the risk properties of the Bitcoin exchange rate versus USD. The Data set is from September 2013 to September 2016 for Bitcoin and the G10 currencies. Empirical findings show Bitcoin returns are much more volatile, much riskier and exhibit heavier tail behaviour than the traditional currencies.

Corbet, Meegan, Larkin, Lucey, and Yarovaya (2018b) examines the return and volatility transmission among three Bitcoin, Ripple and Litecoin, and gold, bond, equities and the global volatility index (VIX). Findings indicate the major cryptocurrencies Bitcoin, Ripple and Lite are interconnected whereas the cryptocurrencies are isolated from other markets. The Bitcoin price can affect the levels of Ripple and Lite and cryptocurrencies may offer diversification benefits for investors in the short term period.

Due to being a new financial instrument, studies related to herding behaviour in the cryptocurrencies market is limited. For instance, Pele and Mazurencu-Marinescu-Pele (2019) investigate the herd behaviour in cryptocurrencies market, especially in Bitcoin by using Metcalfe's law in Bitcoin evaluation, however in the long-run, validity of Metcalfe's law for Bitcoin is debatable.

Vidal-Tomás, Ibáñez, and Farinós (2018) examines the herding in the cryptocurrency market with a dataset of 65 digital currencies from 1 January 2015 to 31 December 2017. Both cross sectional deviations of returns (CSSD) and cross sectional absolute deviation of returns (CSAD) approaches are used in the empirical analysis. The findings indicate that based on both approaches, there is no evidence of herd behaviour in the cryptocurrencies market, showing that the extreme price movements are explained by rational asset pricing models.

Poyser (2018) studies the empirical herding model based on Chang, Cheng, and Khorana (2000) methodology, and developed the model for both under asymmetric and symmetric conditions and the existence of different herding regimes by implementing the Markov-Switching approach. First 100 leading cryptocurrencies are analyzed for the study.

Bouri et al. (2018) examines the existence of herding behaviour in the cryptocurrency market. Cross-sectional absolute standard deviations (CSAD) approach is implemented on 14 leading cryptocurrencies. Based on the CSAD approach, existence of herding cannot be found. As Balcilar, Demirer, and Hammoudeh (2013) has mentioned, the parameters are assumed to be constant over time, which might result in misleading conclusions. For this reason, Bai and Perron (2003), tests are applied for structural breaks. In addition, Stavroyiannis and Babalos (2017) a time varying approach is implemented for a rolling window of 250 observations. Significant herding is found in some rolling windows.

6.3 Data and Methodology

6.3.1 Methodology

Herding behaviour is commonly discussed in financial markets especially for stock markets with different methodologies and definitions (Bikhchandani & Sharma, 2000; Chang et al., 2000; Chiang, Li, Tan, & Nelling, 2013; Demirer & Kutan, 2006; Olsen, 1996). The studies focusing on herding behaviour in cryptocurrencies are conducted by Poyser (2018), and Bouri et al. (2018) by following the similar methodologies of the herding literature.

Many models are generated to measure herd behaviour: Lakonishok, Shleifer and Vishny Measurement (developed by Lakonishok, Shleifer, & Vishny, 1991); Cross Sectional Volatility of Stocks (developed by Christie & Huang, 1995, and Chang et al., 2000); and Beta Herding (developed by Hwang & Salmon, 2004).

This chapter uses Christie and Huang (1995) methodology to detect herd behaviour in cryptocurrency market.

$$\mathrm{CSSD_t} = \sqrt{\frac{\sum_{i=1}^{N}\left(R_{i,t} - R_{m,t}\right)^2}{N-1}} \tag{6.1}$$

$CSSD_t$ stands for the cross-sectional standard deviation of stock return rates from the market return rate in period t. $R_{i,t}$ shows the return rate on i for time t and $R_{m,t}$ shows the return on the market portfolio in time t. N is the number of cryptocurrencies for the selected period.

Christie and Huang (1995) analysed herd behaviour under extreme market conditions with the following regression formula:

$$\mathrm{CSSD_t} = \alpha + \beta_1 D_t^L + \beta_2 D_t^U + \varepsilon_t \tag{6.2}$$

Cryptocurrency daily return is calculated from the following formula:

$$R_{i,t} = \frac{P_{i,t} - P_{i,t-1}}{P_{i,t-1}} \tag{6.3}$$

In Eq. (6.3), $P_{i,t}$ is the closing price of cryptocurrency i on day t and $P_{i,t-1}$ is the closing price of cryptocurrency i on the previous day (t-1). For the 1% upper and lower tails, 15 days of the highest and lowest returns are taken to justify the stress in tails. For the 5% upper and lower tails, 73 days of the highest and lowest returns are taken to show the stress in tails.

In addition to the CCSD methodology, cross-sectional absolute standard deviations (CSAD) is also applied to the same dataset.

$$\mathrm{CSAD_t} = \alpha_0 + \alpha_1 \left|R_{m,t}\right| + \alpha_2 R_{m,t}^2 + \varepsilon_t \tag{6.4}$$

Herding is assumed to be absent if $\alpha_1 > 0$ and $\alpha_2 = 0$. On the contrary, if herding is present, $\alpha_2 < 0$.

6.3.2 Data

The Crypto Currencies (CCI 30) Index is rule based and is delineated to gauge the size and movement of the cryptocurrency market. The index tracks the 30 largest cryptocurrencies by market capitalization. Main characteristics of the index are being diversified, being replicable, being transparent, providing detailed coverage of the whole blockchain sector and presenting the beyond compare risk-adjusted performance figure. The CCI 30 index was started on Jan. 1st, 2015. Constituents of

Table 6.1 Constituents of the crypto currencies index

Bitcoin	NEO
Ethereum	Ethereum Classic
XRP	NEM
EOS	Zcash
Litecoin	Waves
Bitcoin Cash	Tezos
Stellar	VeChain
TRON	Ontology
Binance Coin	Dogecoin
Cardano	Bitcoin Gold
Bitcoin SV	Qtum
Monero	OmiseGO
IOTA	Basic Attention Token
Dash	Zilliqa
Maker	0x

the index are listed in Table 6.1. Cryptocurrencies in the index are put in an order according to their market capitalization, which indicates that Bitcoin has the highest market capitalization, and on the other hand 0x is the last currency with the lowest market capitalization.

Constituents are selected by considering their adjusted market capitalization. Adjusted market capitalization regards volatility as a destabilizing factor in index composition. The index employs an exponentially weighted moving average of the market capitalization to smooth the volatility and achieve the most accurate market capitalization values.

The index value is calculated with the formula below:

$$I_t = \sum\nolimits_{j=1}^{30} W_j \frac{P_j(t)}{P_j(0)} \tag{6.5}$$

Where I_t is the index value at time t, W_j is the weight of the jth name in the index, and P_j is the price of the jth name as a function of time.

Data covers the same period as the index. Daily price data of the cryptocurrencies in the index are gathered from CoinMarketCap. High price fluctuations are noticed on analysed cryptocurrencies (Fig. 6.1).

6.4 Results

Prior to running the regression analyses, preliminary tests should be applied. These preliminary tests include checking the normality with the Jarque-Bera test, testing serial correlation analysed with the Breusch-Godfrey Serial Correlation LM Test and White test is implemented for heteroscedasticity.

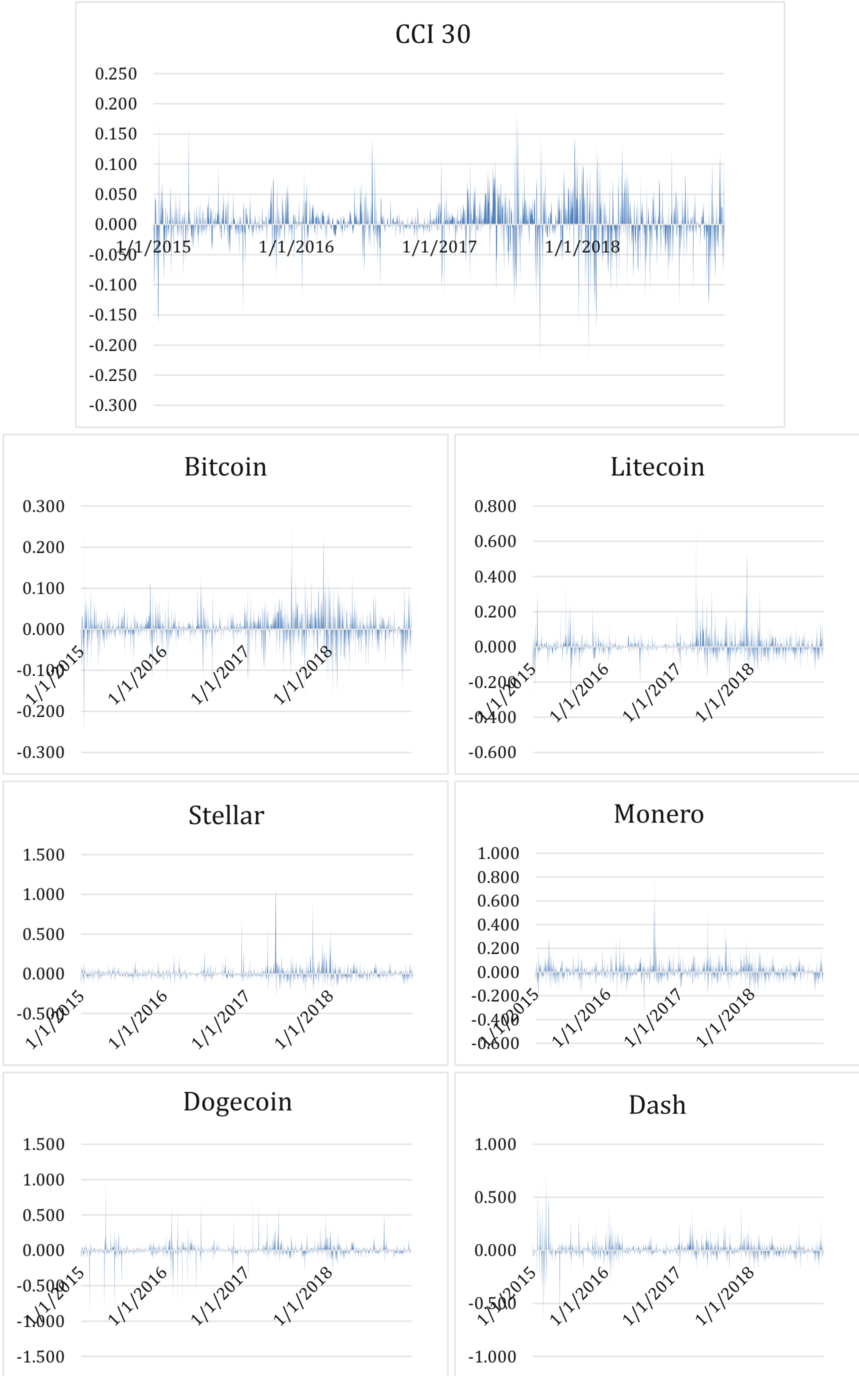

Fig. 6.1 CCI 30 Index and constituents daily return

Table 6.2 Regression results of daily CSSD on market returns

	1% Criterion	5% Criterion
Variables	Coefficients	Coefficients
Included Observations	1459	1459
α	0.062317 (0.0000)	0.059374 (0.0000)
D_t^L (β_1)	0.071806 (0.0000)	0.032540 (0.0000)
D_t^U (β_2)	0.078289 (0.0000)	0.057126 (0.0000)
F-statistic	26.20895	46.44711

Table 6.3 Regression results of daily CSAD on market return

Variables	Coefficients
Included Observations	1459
α	0.036052 (0.0000)
α_1 ($\lvert R_{m,t} \rvert$)	0.379745 (0.0010)
α_2 $\left(R^2_{m,t}\right)$	0.151303 (0.8591)
F-statistic	33.51159

After the preliminary analysis, regression Eq. (6.2) was run to find out the presence of herd behaviour cryptocurrency market.

Table 6.2 shows the results of estimated coefficients for CSSD of returns during the period Jan 1, 2015 and December 31, 2018. The data is consisted of 1459 daily return for 6 cryptocurrencies that were in market during the given period. The (β_1) coefficient indicates the change in the amount of return dispersion given that cryptocurrency return is in the lowest 1 and 5% return, which is mentioned as lower market stress. On the other hand, the (β_2) coefficient shows the change in the amount of return dispersion given that cryptocurrency return is in the highest 1 and 5% return, which is also mentioned as upper market stress. The lowest and highest 1 and 5% refer to the extreme price movement days that lie in the upper and lower tails of the market return distribution.

Table 6.2 indicates the β_1 and β_2 coefficients of the regression analysis for CSSD. Negative value of β_1 is assumed as a proxy of herd behaviour existence. On the contrary, positive β_1 and β_2 coefficients are predicted as rational asset pricing models. According to Table 6.1, β_1 coefficient is not negative, but statistically significant in both 1 and 5% extreme tails. Findings show that there is no evidence of herd behaviour in the cryptocurrency market.

Table 6.3 shows the regression results for CSAD method. A positive and statistically significant α_1 coefficient shows that CSAD returns on cryptocurrencies is an increasing function of absolute value of markets returns.

Herding is assumed to be absent if $\alpha_1 > 0$ and $\alpha_2 = 0$. On the contrary, if herding is present, $\alpha_2 < 0$. Based on the findings of Table 6.2, α_2 is positive, which means that with the CSAD method herding is not present in the cryptocurrency market.

6.5 Conclusion

Behavioral issues in the field of finance has gained importance in the last few decades as the traders started to behave irrationally and disagree with the rational asset pricing models. Herding behavior is just one of the behavioral finance topics which has gotten the attention of researchers especially for stock markets. Cryptocurrencies are the other trending topic in financial markets. This chapter focuses on herding behaviour in the cryptocurrency market, considering CSSD and CSAD approach for cryptocurrencies in CCI 30 Index.

CSSD results indicate that during the period from January 1, 2015 and December 31, 2018, there is no evidence of herd behaviour in the cryptocurrency market when CCI 30 index is taken as market portfolio for both 1 and 5% extreme tails.

CSAD findings also show that, α_2 coefficient which is accepted as a proxy for herding behaviour is positive, but not statistically significant. Overall, given the findings of both methodologies, there is not statistically significant evidence that shows the presence of herd behaviour in the cryptocurrency market.

The findings of the both approaches are in line with the findings of the previous literature regarding the herding behaviour in cryptocurrencies. Bouri et al. (2018) and Vidal-Tomás et al. (2018) also investigates the herding behaviour in cryptocurrencies and in both studies empirical findings indicate the absence of herd behaviour in CSAD and CSSD methodologies, which can be interpreted as extreme price movements are explained by rational asset pricing models, just like the findings of this paper.

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