University of Pretoria
Department of Economics Working Paper Series

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Working Paper: 2018-34
June 2018

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Abstract

This study examines the presence of herding in the cryptocurrency market. The latter is the outcome of mass collaboration and imitation. Results from the static model suggest no significant herding. However, the presence of structural breaks and nonlinearities in the data series suggests applying a static model is not appropriate. Accordingly, we conduct a rolling-window analysis, and those results point to significant herding behavior, which varies over time. Using a logistic regression, we find that herding tends to occur as uncertainty increases. Our findings induce useful insights related to portfolio and risk management, trading strategies, and market efficiency.

Keywords: Bitcoin; cryptocurrency market; herding behavior; economic policy uncertainty.

JEL codes: C22; G13.

1. Introduction

Throughout history, *herd investing*[1] has been thought to intensely affect movements in markets, ranging from the Dutch tulip mania of the 1630s, to the dynamics that triggered the 2007 housing market crisis, and, of course, the "dot-com" bubble of the early 2000s. While herding behaviour has often been studied empirically in financial markets (Economou et al., 2011; Yao et al., 2014), it remains unexplored in the controversial cryptocurrency market that currently piques many individual investors' interest. Like Bitcoin, most cryptocurrencies exhibit extraordinary returns and extreme volatility without obvious justifying news. Furthermore, the cryptocurrency market is characterized by a weak legal framework and a lack of quality information. Inexperienced investors who rely on this information then venture into Bitcoin and other cryptocurrencies without fully understanding the risks[2]. Often, they are influenced by others[3] regardless of their own analysis, which points to potential herding behaviour, possibly intensified by uncertainty and extreme market conditions.

This study contributes to the rising debate on the cryptocurrency market investment from a behavioural finance perspective, specifically analyzing herding behaviour. Studying herding behaviour in the cryptocurrency market is crucial for several reasons. First, it offers a behavioural explanation for the extreme volatility and trends observed in many cryptocurrencies. Herding affects the risk-return tradeoff and thus entails implications for asset pricing (Gębka and Wohar, 2013; Yao et al., 2014). Second, herding behaviour can explain bubbles and crashes (Avery and Zemsky, 1998), two features of cryptocurrency markets' short history (Cheah and Fry, 2015; Fry and Cheah, 2016; Corbet et al., 2017). Herding is thought to seriously intensify the volatility of asset returns and destabilize the financial system (Demirer and Kutan, 2006), and therefore, is of high importance to policy makers. It leads to the suppression of private information, which undermines the ability of the market to reflect fundamental information and thus challenges the efficiency of markets (Hwang and Salmon, 2004; Yao et al., 2014).

Following the approach of Chang et al. (2000), a static model analysis shows no herding in the cryptocurrency market. However, a rolling analysis (Stavroyiannis and Babalos, 2017)

[1] We refer to a simple definition of herding according to Hwang and Salmon (2004). It is when investors imitate the investment decisions of others without reference to fundamentals.

[2] Those inexperienced investors seem to have a dispersion in their information that makes them expect extreme outcomes to occur more likely than moderate ones.

[3] When for instance founders of leading cryptocurrencies like Vitalik Buterin and Charlie Lee or analysts like Alex Sunnarborg and Spencer Bogart express their opinion on specific cryptocurrencies, they affect cryptocurrencies prices.

provides evidence in favor of herding, suggesting that crypto traders mimic the investment decisions of others, as in imperfect learning systems. However, herding behavior appears to be time-varying and mostly driven by economic policy uncertainty.

The rest of the paper proceeds as follows. Section 2 presents the research background. Section 3 provides the data and methods. Section 4 presents empirical results. Section 5 concludes.

2. Research background

Built on a shared and encrypted database technology, called the "blockchain", Bitcoin was implemented in early 2009. Its underlying technology inspired a new generation of cryptocurrencies, developed mostly through imitation, from 2011-12. Since then, the cryptocurrency market has never settled but has evolved into a new asset class and become a fashionable investment choice. It induces tremendous attention from portfolio investors due to its low correlation with conventional assets (Bouri et al., 2017; Corbet et al., 2018). However, the cryptocurrency market still lacks maturity, market depth, regulations, and, to some extent, transparency[4]. Furthermore, uncertainty among crypto traders, such as the dispersion of information, characterises decision-making.

Unlike with equities, there is no consensus on how to value a cryptocurrency, so practitioners' opinions widely vary, with some viewing Bitcoin and other cryptocurrencies as fraudulent and some as the currency of the future. Because of this controversy, financial analysts rarely recommend or rate cryptocurrencies; therefore, cryptocurrency markets are highly dependent on socially-constructed opinions. Furthermore, many participants in the cryptocurrency markets are individual investors, mostly young and inexperienced[5], who rely on social media and online chat forums for research, and thus are easily persuaded. Greed combined with the fear of missing out on a great gain can drive cryptocurrencies to unjustified price levels[6]. The extreme speculative nature of the largest cryptocurrency, Bitcoin, (Baur et al., 2018), makes the cryptocurrency markets highly volatile, which potentially leads to herding. Furthermore, and unlike with equities, traders in cryptocurrencies are not as sensitive to negative shocks, which does not easily trigger high selling in the cryptocurrency market[7].

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[4] While Dimpfl (2017) provides evidence on the transparency of the Bitcoin market through the continuous release of information on the order book, this might not be the case for other cryptocurrencies.

[5] According to Menkhoff et al. (2006), herding decreases with experience.

[6] Bitcoin price depends less on economic and financial variables (Kristoufek, 2015) and more on a unique set of characteristics such as attractiveness (Kristoufek, 2015), energy prices (Li and Wang, 2017), user anonymity (Ober et al., 2013), computer programming enthusiasts and illegal activity (Yelowitz and Wilson, 2015).

[7] The fact that short selling is not allowed on most cryptocurrencies might have played a role in limiting the selling pressure in the cryptocurrency market.

Herding requires the coordination of a price movement or the ability to observe the actions of others (Devenow and Welch, 1996). Such mechanisms are available in the cryptocurrency market, which has definitely benefited from the internet era where social media and networks easily allow the sharing of information and ideas. Interestingly, it is easy to observe the trading actions of big cryptocurrency holders, called "whales" using "cryptocurrency whale watching" applications and websites[8] that allow users to follow those whales and thus their trading actions. Furthermore, Bitcoin and other cryptocurrencies are not considered to be securities, suggesting that the sharing of information is legal.

3. Data and testing methodology

3.1 Data

Our study focuses on 14 leading cryptocurrencies (Bitcoin, Ethereum, Ripple, Litecoin, Stellar, Dash, Nem, Monero, Bytecoin, Verge, Siacoin, BitShares, Decred, and Dogecoin) that constitute 68.36% of the overall cryptocurrency market capitalization. After considering the 50 largest cryptocurrencies (https://coinmarketcap.com/), we kept these 14 cryptocurrencies because their price data covers at least a 2-year period; we wanted a wider time span to make the most of our empirical analysis. The sample period is from 28/04/2013 to 02/05/2018, with a total number of 1,830 observations. The source for the closing prices of the various cryptocurrencies is https://coinmarketcap.com/.

3.2 Testing methodology

Following the approach of Chang et al. (2000), we use the cross-sectional absolute standard deviations (CSAD) among 14 cryptocurrencies to define the non-linear relation between the level of cryptocurrency return dispersions and the overall cryptocurrency market return. The CSAD statistic, used as a measure of return dispersion, is formulated as follows:

$$CSAD_t = \frac{1}{N}\sum_{i=1}^{N} | R_{i,t} - R_{m,t} | \tag{1}$$

where $R_{i,t}$ and $R_{m,t}$ is the return on cryptocurrency *i* and the value of a weighted average (based on their percentage of total market capitalization) of all 14 cryptocurrencies returns for period *t*,

[8] https://www.cryptostache.com/2017/11/21/cryptocurrency-whale-watching/

respectively; N is the number of cryptocurrency in the portfolio at time t.[9]

Chang et al. (2000) suggests that during periods of market stress, one would expect return $CSAD_t$ and $R_{m,t}$ has a nonlinear relationship. Christie and Huang (1995) suggest that the probability of herd behaviour increases during periods of market stress and large price movements. Therefore, we have a benchmark model based on the following quadratic model of return dispersion and market return:

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

The presence of herding is tested through the following hypotheses:

H_0: In the absence of herding effects, we expect in the Eq. (2) that $\alpha_1>0$ and $\alpha_2=0$

H_{11}. If herding behaviour exists, we expect $\alpha_2<0$.

H_{12}. If anti-herding behaviour exists, we expect $\alpha_2>0$.

4. Results

The results from the static model in Eq. (2) are reported in Table 1. First, the coefficient α_1 is positive and statistically significant, meaning that the $CSAD_t$ of returns on cryptocurrencies is an increasing function of the absolute value of market returns ($|R_{m,t}|$). Second, there is evidence of anti-herding behaviour, as illustrated by the statistically significant coefficient (α_2) on the squared market returns, i.e., $R^2_{m,t}$.

[INSERT TABLE 1]

It is argued that the static model in Eq. (2) leads to misleading conclusions regarding herd behaviour, as parameters are assumed to be constant over time (Balcilar et al, 2013). To verify this line of reasoning, the powerful tests of Bai and Perron (2003) are applied to Eq. (2), to detect 1 to M structural breaks, allowing for heterogeneous error distributions across the breaks. Based on these tests, five breaks are detected at: 14/05/2014, 13/02/2015, 17/11/2015, 12/09/2016, and 15/06/2017, as shown in Table A1 in the Appendix. In addition, the nonlinearity test of Brock et

[9] Note that, not all cryptocurrencies cover the entire period of the analysis. Hence, the *CSAD* and $R_{m,t}$ are computed accordingly for a specific day based on the available data on the number (N) of cryptocurrencies on that day. All the 14 cryptocurrencies are available from 10/02/2016. The starting dates of each cryptocurrencies are as follows: Bitcoin: 28/04/2013; Ethereum: 07/08/2015; Ripple: 04/08/2013; Litecoin: 28/04/2013; Stellar: 05/08/2014; Dash: 14/02/2014; Nem: 01/04/2015; Monero: 22/05/2014; Bytecoin: 17/06/2014; Verge: 25/10/2014; Siacoin: 27/08/2015; BitShares: 21/07/2014; Decred: 10/02/2016; and Dogecoin: 15/12/2013.

al., (1996), called the BDS test, is applied to the residuals of the static model in Eq. (2). Results obtained[10] show strong evidence (at highest level of significance across all possible dimensions) of nonlinearity. Together, the structural breaks and nonlinearities confirm the unreliability of the static model in Eq. (2) and its results.

Given this, we resort to a time-varying approach (Stavroyiannis and Babalos, 2017) based on a rolling window of 250 observations, which essentially covers the number of data points for the year 2013. The size of the window makes sense, as the earliest break date was obtained much later, at the 381st observation, i.e., 14/05/2014. Figure 1 presents the rolling *t*-statistics, with the 5% critical value of ± 1.96. The figure shows prolonged periods of anti-herding at the early (03/01/2014-25/08/2014), middle (08/08/2015-13/04/2016), and end (27/03/2018-02/05/2018) of the sample period. However, unlike the full-sample estimation emanating from the static model, herding is observed, in general, over 14/04/2016 to 21/01/2018, and in the early part of the sample covering 26/08/2014-05/11/2014 and 16/12/2014-03/02/2015, but in the latter case, it is statistically insignificant.

Significant herding is detected over 24/04/2016-28/11/2016, 05/01/2017-01/04/2017, 21/05/2017-29/05/2017 and 20/07/2017-13/09/2017, i.e., primarily over the period from April 2016 to September 2017. First, evidence of herding is expected in the new and fast-expanding cryptocurrency market due to its extreme price volatility, lack of quality information, and the tendency of crypto traders to expect extreme positive outcomes. Evidence of herding implies that the trading decisions of crypto traders are not made in isolation. Instead, crypto-traders ignore the individual characteristics of cryptocurrencies and herd on the performance of the cryptocurrency market. It seems that crypto traders exhibit an illusionary belief that cryptocurrency prices will not fall in the near future. Demirer and Kutan (2006) argue that this finding partially explains the high levels in market volatility. Second, it is not surprising for herding to follow a dynamic pattern as investor behaviour, including herding, can change over time (Gębka and Wohar, 2013).

A crucial question to ask is: What can explain significant herding over that period? Balcilar and Demirer (2015) relate herding to uncertainty. Given this, we define a dummy variable, which takes a value of 1 during periods of statistically significant herding (i.e., for months when the rolling *t*-statistic on α_2 <-1.96) and zero otherwise, and then, we use a Probit model to relate this dummy with the news-based economic policy uncertainty (EPU) index of the US, as developed by Baker et al., (2016). Note that, the decision to use the US EPU instead of global uncertainty is primarily due to the lack of data availability on such a measure at daily

[10] The result of the BDS test is reported in Appendix Table A2.

frequency. Also, the importance of the US economy to global financial markets is quite well-accepted, and hence the US EPU can be considered a reliable approximation of global risk. More importantly, the role of US EPU in affecting the cryptocurrency (in particular, Bitcoin) has been recently stressed by Demir et al., (2018). The results from the Probit model are reported in Table 2. As can be clearly seen, EPU increases the probability of herding, in a statistically significant manner at the highest level of significance.[11] In other words, economic uncertainty tends to drive herding in the cryptocurrency market. This implies that in the presence of higher economic policy uncertainty, crypto traders become more confident about the (upward) direction of cryptocurrencies and thus tend to mimic the trading actions of others. This is in line with evidence that Bitcoin and the overall cryptocurrency market exhibit a safe-haven property that prevent crypto traders from engaging in "flight to safety" during the presence of economic policy uncertainty, which is contrary to the case of equity markets (Bouri et al., 2017).

[INSERT FIGURE 1]

5. Concluding remarks

Inspired by the methods of Chang et al. (2000) and Stavroyiannis and Babalos (2017), we conduct an empirical study and showed that the cryptocurrency market is subject to herding behaviour that seems to vary over time. Evidence of the high degree of co-movement in the cross-sectional returns' dispersion across cryptocurrency markets implies that crypto traders mimic the investment decisions of others. This has implications on portfolio and risk management inferences. Evidence of herd investing suggests insufficient portfolio diversification and thus the exposure of investors holding only cryptocurrencies to additional risk. Contrarian investing cannot be profitable if herd behavior prevails for significant periods of time. Such an implication should be considered in future research.

Regarding policy makers, evidence of herding is indicative of relative market inefficiencies. It makes the occurrence of systematic risk more likely, which could jeopardize market stability, a strong and wide concern for policy-makers. Therefore, stricter market regulations that reduce herding behaviour and promote market efficiency are called for. The potential subsequent arrival of more institutional investors to the crypto world would also bring

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[11] An informal analysis over the period of April 2016 to September 2017, i.e., when we observed significant herding primarily, showed that the correlation between the rolling herding coefficient and the EPU was positive (0.0072) and significant at the 1% level (*p*-value of 0.0098). In addition, note that, our results from the Probit model were qualitatively similar, if we defined the dummy variable to take a value of 1 whenever the rolling *t*-statistic on α_2 was negative, irrespective of significance. Complete details of all these results are available upon request from the authors.

more rational cryptocurrency players and analysts, potentially reducing highly speculative trading activities.

While this study applies an approach of Chang et al. (2000) to measure herding, the application of other approaches might offer further insights into the investment behaviour of crypto traders.

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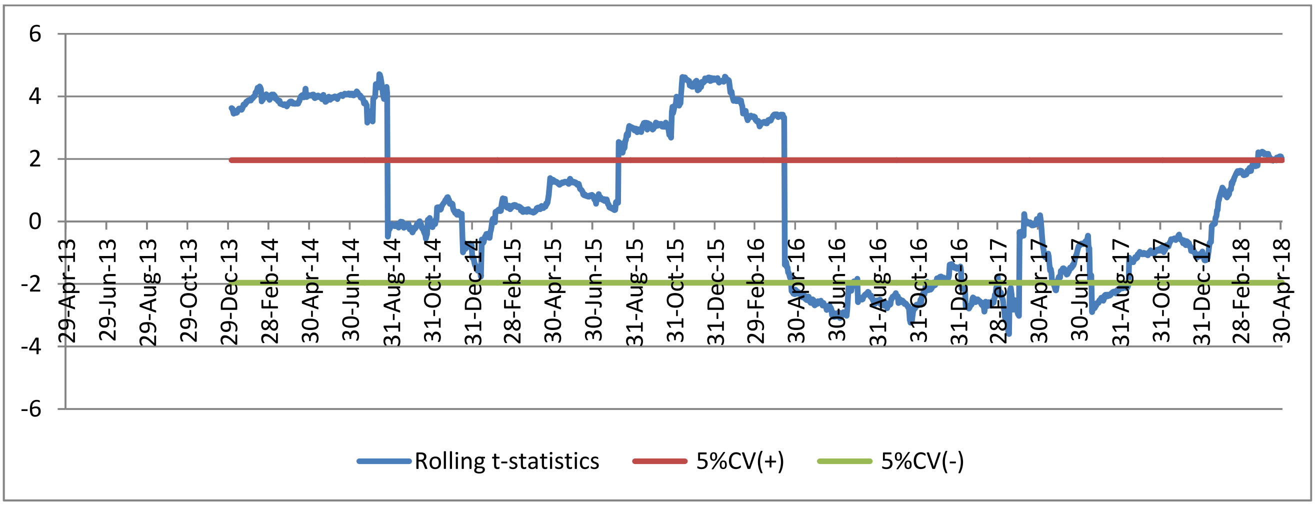
Table 1. Estimates of the static model

α_0	α_1	α_2	RSS	LogL	AIC	adj.R^2
0.0366***	0.6190***	1.9520***	1.4947	-3911.7320	4.2695	0.2456

Notes: The table reports the estimates for CSAD in Equation (2). All estimations are done using the ordinary least squares (OLS). RSS denotes residual sum of squares, log L denotes log likelihood of the OLS model, AIC denotes the Akaike information criterion, and adj. R^2 denotes the adjusted coefficient of determination. *** represent significance at the 1% level. A significant and positive α_2 estimate implies anti-herding behaviour.

Figure 1. Rolling *t*-statistic based on a rolling-window (250 observations) estimation of the static model



Note: 5%CV(+) stands for 1.96, while 5%CV(-) is equal to -1.96.

Table 2. Estimates of the Probit model

Variable	Coefficient	S.E.	*z*-Statistic	*p*-value
EPU	0.0043	0.0008	5.6631	0.0000
c	-1.1014	0.0728	-15.1391	0.0000
McFadden R^2	0.0194			
RSS	272.2046			
Akaike info criterion	1.0562			
LogL	-832.9195			
Observations with Dependent Variable (Dep)=0	1219			
Observations with Dep=1	361			

Note: Method: ML - Binary Probit (Newton-Raphson / Marquardt steps); Convergence achieved after 3 iterations; Coefficient covariance computed using observed Hessian.

APPENDIX:

Table A1. Bai and Perron (2003) Tests of Multiple Structural Breaks in Equation 2 (Static Model)

1 to *M* globally determined breaks					
Break test options: Trimming 0.15, Max. breaks 5, Sig. level 0.05					
Allow heterogeneous error distributions across breaks					
Sequential F-statistic determined breaks:				5	
Significant F-statistic largest breaks:				5	
UDMax determined breaks:				1	
WDMax determined breaks:				1	
Breaks	*F*-statistic	Scaled *F*-statistic	Weighted *F*-statistic	Critical Value	
1 *	46.5728	139.7183	139.7183	13.98	
2 *	33.9213	101.7638	118.6537	11.99	
3 *	25.5712	76.7135	103.2199	10.39	
4 *	21.1189	63.3567	97.8703	9.05	
5 *	18.3328	54.9984	103.0667	7.46	
UDMax statistic		139.7183	*UDMax* critical value		14.23
WDMax statistic		139.7183	*WDMax* critical value		15.59
Estimated break dates:					
1: 13/05/2014					
2: 09/02/2014, 13/07/2017					
3: 13/05/2014, 15/08/2016, 15/07/2017					
4: 14/05/2014, 13/02/2015, 12/09/2016, 15/06/2017					
5: 14/05/2014, 13/02/2015, 17/11/2015, 12/09/2016, 15/06/2017					

Table A2. BDS Test on Residuals of Equation 2 (Static Model)

Dimension (*m*)	BDS Statistic	Std. Error	*z*-Statistic	*p*-value
2	0.0370	0.0021	17.4401	0.0000
3	0.0634	0.0034	18.8012	0.0000
4	0.0786	0.0040	19.5954	0.0000
5	0.0852	0.0042	20.3923	0.0000
6	0.0867	0.0040	21.5265	0.0000

Notes: *m* stands for the number of (embedded) dimension which embed the time series into *m*-dimensional vectors, by taking each *m* successive points in the series. The BDS *z*-statistic tests for the null of *i.i.d.* residuals.