UNCERTAINTY AND HERDING BEHAVIOR: EVIDENCE FROM CRYPTOCURRENCIES

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Abstract

The aim of this study is to examine the existence of herding behavior in the cryptocurrency market under uncertainty by employing cross-sectional absolute deviation (CSAD) of returns, ordinary least squares (OLS), generalized autoregressive conditional heteroscedasticity (GARCH) methods and Time-Varying Markov-Switching (TV-MS) model for both overall sample and sub-periods which was determined based on the results of Quandt-Andrews and Bai-Perron breakpoint tests. We utilized the daily data of the 14 leading cryptocurrencies in terms of closing price, market cap and transaction volume. We also used dummy variables to analyze whether or not an asymmetric behavior occurred during the "up and down" market periods. Our results for the overall sample refer to an anti-herding behavior in each model. However, the results of the TV-MS model for the 3rd sub-period (2/28/2017-1/16/2018) imply the existence of a herding behavior in the low volatility regime, an anti-herding behavior occurred during the high volatility regime and the effect of uncertainty was significant on the anti-herding behavior. Finally, our results suggest that there was no significant asymmetric behavior during the "up and down" market periods.

Key words: Herding; uncertainty; cryptocurrency market; behavioral finance; time varying Markov-switching

JEL Codes: G41, D81, C58.

1. INTRODUCTION

It has been first considered by philosophers in ancient Greek that a man makes decisions due to both intelligence and desires which determines his character. According to Aristotle, a rational action is explained by showing that it achieves some end sought by desire (Irwin, 1975). In parallel with early Greek thoughts, all agents are assumed to be rational and optimize their utility across a variety of choices which is known as "rational choice theory" or "expected utility theory" in mainstream economics. Relevant theories suggest that all agents make rational decisions by

considering the highest expected utility. Innocenti and Sirigu (2012) state that expected utility theory indicates how an individual should choose in order to be considered rational, but it is not truly informative about how people actually decide in real life, or why they frequently violate such normative prescriptions. On the other hand, according to Fama's (1970) efficient market hypothesis all investors are assumed to be fully rational at their investment decisions. As suggested by Fama (1970), in an efficient market, investors cannot yield above the average price through the use of relevant information, since the price fully reflects all publicly available information. However, Akerlof (1978) developed a new theory based on "asymmetric information" and "adverse selection" which explains market mechanism from a more realistic point of view. Akerlof (1978) contributed to the theory of decision making by considering the effect of uncertainty in the markets instead of fully informed rational agents. Simon (1972) also contributed to modern economics with the theory of "bounded rationality" which suggests that risk and uncertainty can be introduced into the demand function, the cost function or both.

In recent years, there has been an increasing interest in the theories of decision-making and alternative approaches to behavior of agents. A number of researchers have reported controversial findings which indicate irrational behaviors of investors. For instance, Tversky and Kahneman (1979, 1992) proposed a new theory called "prospect theory" which has two key elements: i) a value function that is concave for gains, convex for losses, and steeper for losses than for gains, ii) a nonlinear transformation of the probability scale, which overweights small probabilities and underweights moderate and high probabilities. Moreover, according to certainty effect phenomenon people overweight outcomes that are considered certain, relative to outcomes which are merely probable. Tversky and Kahneman (1974, 1992) argues that a change from impossibility to possibility or from possibility to certainty has a bigger impact than a comparable change in the middle of the scale¹. As it is also stated in Tversky and Kahneman (1992), risk aversion for gains is more pronounced than risk seeking for losses, for moderate and high probabilities. By extending the prospect theory to uncertain as well to risky prospects with any number of outcomes Tversky and Kahneman (1992) suggested a new model called "cumulative prospect theory" and it provides a unified treatment of both risk and uncertainty.

A number of empirical studies have revealed that markets may not be efficient depending on investors' irrational decisions under uncertainty. If investment decisions are based on information from others rather than the investor's information, a herd behavior may occur in the market. Herding as an irrational behavior causes increase in volatility and instability in the markets. Galariotis et al. (2016) suggested that irrational herding is a key factor for the financial turmoil and the soaring yield spreads. Thaler (2005) also suggests that short-sale constraints with irrational traders, can cause some stocks to become overpriced (see, e.g., Miller 1977, Russell and Thaler 1985, and Chen et al., 2002). Moreover, irrationality/herding may deepen the fragility of the

¹ Tversky and Kahneman (1992) state that an increase of .1 in the probability of winning a given prize has more impact when it changes the probability of winning from .9 to 1.0 or from 0 to .1, than when it changes the probability of winning from .3 to .4 or from .6 to .7. Therefore, diminishing sensitivity, gives rise to a weighting function that is concave near 0 and convex near 1.

financial system and may also lead to a bubble/crash (see; e.g., Spyrou, 2013; Kristoufek, 2013; Balcilar and Demirer, 2015; Galariotis et al., 2016; among others).

Our motivation for the study was to examine the herding behavior in cryptocurrencies which are hard to value growth options/intangible assets and this might lead to herding among investors. According to the theory of Daniel, Hirshleifer, and Subrahmanyam (1998), informed traders attribute their own positive performance to their own skills, thus making themselves overconfident and overconfidence further produces momentum (Yang, 2019). The momentum effect is strong for stocks that are difficult to value, such as those with high R&D expenditures or intangible assets (Einhorn, 1980; Daniel and Titman, 1998; Daniel, Hirshleifer, and Subrahmanyam, 1998). Moreover, dramatic price increases in crypto-currencies may attract the attention of noise traders (see, Piccoli and Chaudhury, 2019; Kristoufek, 2013), however Baur and Dimpfl (2018) provide evidence that the largest crypto-currencies (Bitcoin and Ethereum) are dominated by informed investors. Kristoufek (2013) suggests that as there are no macroeconomic fundamentals for the digital currencies, there is no fundamental value and the demand side of the market is not driven by an expected macroeconomic development of the underlying economy but it is driven only by expected profits of holding the currency and selling it later (as there are no profits due to no interest rates of the digital currencies). Therefore, the market is dominated by short-term speculators. Regardless of which type of investor dominates the market, Cheah and Fry (2015) found that Bitcoin prices contain a substantial speculative bubble component and more importantly, their results show that the fundamental value of Bitcoin is zero. Cheung et al., (2015) argues that bitcoin is hard to value as it does not have any clearly identifiable cash flows additionally it is not even clear what its nature is. It has no intrinsic value and its value simply depends mostly on its speculative value (Cheung et al., 2015). Empirical findings of Barber et al., (2009) also indicates that individual investor lose from trade, while institutions profit in cryptocurrency market.

In terms of a herding measure, Christie and Huang (1995) measured return dispersion and used two dummy variables to capture the herding by using cross-sectional standard deviation (CSSD) during periods of extreme market returns and large price movements as they argued in the study that the probability of herd behavior increases in such periods. Chang et al. (2000) proposed a further developed measure of return dispersion called cross-sectional absolute deviation (CSAD) (Chen et al., 2017). Chang et al. (2000) suggested that during periods of market stress, one would expect return dispersion (i.e. $CSAD_t$) and market return (i.e. $R_{m,t}$) to have a nonlinear relationship. Therefore, we employed a benchmark model based on the two-state Markov regime shift model developed by Hamilton (1989) and Hansen (1992) to analyse the dynamic behavior of herding. As it is stated in Babalos et al., (2015), the regime-switching framework appears to capture the dynamic behavior of herding phenomenon and fits into the logic behind the testing methodology of herding which is built on the relationship between return dispersions and market returns during the periods of market stress. Moreover, the regime-switching model also allows the detection of evidence of negative herding (or anti-herding behavior).

Since previous studies of herding behavior in cryptocurrencies market did not deal with regime dependence, in the present study, we estimated the transition probabilities of herding behavior for low and high volatility regimes and the expected durations of each regime by considering the economic policy's uncertainty effect on the market. Our results indicated both herding and anti-herding behavior in different sub-periods and regimes. The present paper is organized as follows: section 2 provides the literature review related to the herding behavior in cryptocurrencies and regime-switching models that have been applied to capture herding behavior in different markets. In the next section a brief description of the data is given and modelling strategies are explained. Thereinafter, section 4 analyzes and discusses the empirical results. Finally, section 5 gives a summary of the discussion and concludes.

2. LITERATURE REVIEW

The behavior of an individual and a group may differ in some cases. Shiller (1995) indicates that people who interact with each other regularly tend to think and behave similarly. The tendency for people in groups to think and behave similarly suggests some kind of irrationality. Leibenstein (1950) who introduced the social psychological bandwagon metaphor in economics, explained the motivations underlying herd behavior as “the desire of people to purchase a commodity in order to get into 'the swim of things'; in order to conform with the people, they wish to be associated with; in order to be fashionable or stylish; or, in order to appear to be 'one of the boys.’” Moreover, information asymmetries between retail investors and institutional investors, lack of transparency and information disclosure, low trading volume, inadequate regulatory framework, etc. may promote and facilitate herding behaviour (Kallinterakis and Kratunova 2007).

Graham (1999) emphasized that there are four types of herding: i) informational cascades, ii) reputational herding, iii) investigative herding, and iv) empirical herding. According to Graham (1999) the first two types of herding are observed when individuals choose to ignore or downplay their private information and jump on the bandwagon by mimicking the actions of individuals who acted previously. Informational cascades occur when the existing aggregate information becomes so overwhelming that the individual's single piece of private information is not strong enough to reverse the decision of the crowd. Thus, the individual chooses to mimic the action of the crowd, rather than act on her private information (Graham, 1999). Hirshleifer and Teoh (2003) reviewed herding types and referred that reputational herding and dispersion is convergence or divergence of behaviour depending on the attempt of an individual to maintain a good reputation with another observer. Bikhchandani and Sharma (2000) cited in Spyrou (2013) distinguish between “spurious herding” and “intentional herding”. Spurious herding is defined as where investors take similar decisions because they face similar information sets and react to the same changes in fundamental factors and intentional herding is defined as where investors copy each other's actions with intent. Kallinterakis and Gregoriou (2017) identified two distinct types of intentional herding: informational and professional. Informational herding occurs when an investor believes that she has an informational disadvantage and copies other investors' trading. Professional herding is observed among investment professionals, such as fund managers and financial analysts. Low

skilled managers tend to mimic the trades of highly skilled managers. According to Graham (1999), investigative herding occurs when a financial analyst prefers to investigate a piece of information about an asset that she believes others also will examine and push the price of the asset in the direction anticipated by the first analyst. Empirical herding is another classification type of herding by Graham (1999) which he groups the studies that investigate empirical clustering without directly testing the implications of the herding models. SgROI (2004) refers to sequential herding what Graham titles as reputational herding and states that when herding begins public information will swamp private information and all later decision makers will copy the actions of their predecessors. On the other hand, from a different point of view, Rook (2006) noticed that herd behavior could lead to "path dependence" in the sense that the good that was adopted first because of an early historical event could obtain an irreversible first mover advantage. Path dependence may also prevent from breaking the herd. Consequently, irrationality arising from herding behavior may cause markets to be inefficient in the sense of Fama's (1970) efficient market hypothesis.

A considerable amount of literature has been published on herd behavior in financial markets. These studies show the importance of an irrational herding which can cause various problems in the markets. It is essential to ascertain herding behavior in a financial market because it may lead to an inaccuracy in the calculated value of asset prices and it may affect expected returns of assets under financial risk management and investment assessments. A number of studies revealed that herd behavior may be observed in different markets such as stock markets, commodity markets, oil markets, cryptocurrency markets, REITs in different volatility regimes.

Following Chiang et al. (2007), the dynamic behavior of stock market volatility is analyzed by Diamandis (2008) for four Latin American stock markets (Argentina, Brazil, Chile and Mexico) and a mature stock market, that of the US. According to the model results, because the correlations between stock returns and their volatility are consistently higher, herding behavior was detected in stock markets. Balçilar and Demirer (2015), tested the dynamic relationship between global factors and herd behavior in an emerging market Borsa Istanbul by utilizing a time-varying transition probability Markov-switching model. Findings of the study reveal that herd behavior occurs during both the high- and extreme-volatility regimes.

To estimate the herding behavior of US-listed Real Estate Investment Trusts (REITs), Babalos et al., (2015) employed a static herding model and a Markov regime-switching model. The findings reveal that static herding model rejects the existence of herding in REITs markets however the estimates of the regime-switching model reveal substantial evidence of herding behavior under the crash regime for almost all sectors. On the other hand, a shift from negative herding behavior during low and high volatility regimes to positive herding behavior is observed under crash regime for almost all REITs sectors. Using a vector Markov-switching model of Hamilton and Lin (1996), Balagyozyan and Cakan (2016) investigate whether and to what extent large institutional investors herded during the buildup and collapse of the dot-com bubble of the 1990s. Their findings suggest that herding was much more prevalent during the run-up of the bubble than during the collapse. To examine the herding behavior in the context of ethical investments under the screening of Shariah

Stavroyiannis and Babalos (2017) used a large dataset of the components stocks of the U.S. Islamic Dow Jones for a period extending from January 2007 to December 2014. They utilized a variety of static and time-varying methods and according to the results of rolling window and time-varying parameter regression models the components of the U.S. Islamic Dow Jones do not exhibit herding behavior but an anti-herding behavior. Results from the rolling-window analysis reveal that anti-herding tends to be more intense during turbulent periods.

By utilizing a regime-switching model, Demirer et al., (2015) tested the presence of herd behavior in a number of commodity sectors including energy, metals, grains and livestock during the low and high market volatility states. Empirical results of the study imply a herd behavior in grains only during the high volatility state. Moreover, large price movements in the energy and metal sectors contribute to herd behavior in the market for grains. Balcilar et al., (2014) examined the relative roles of a market's own volatility and global factors in driving herd behavior in developing stock markets, with a focus on the cash- and oil-rich Gulf Cooperation Council (GCC) stock markets. Results of the study suggest that herd behavior is a dynamic phenomenon but not observed in all periods and it evolves in a smooth regime switching fashion. Moreover, market volatility is the most significant variable driving regime switching between the extreme states of non-herding and herding.

Several attempts have been made to analyze the existence of herding behavior and its effects on financial markets (Banerjee, 1992; Balcilar and Demirer, 2015; Galariotis et al., 2016; Clements et al., 2017; Economou et al., 2018 among others). As it is stated above, herding behavior leads inefficiencies in the financial markets. There are a large number of empirical studies which attempt to highlight the efficiency of cryptocurrency market. Urquhart (2016) was first to test weak form efficiency of Bitcoin through a battery of robust tests. The data used in the study consists of daily closing prices for Bitcoin in USD from 1st August 2010 to 31st July 2016. The results indicate that Bitcoin market is not weakly efficient over the full sample period but when the sample is splitted into two subsamples (1. Subsample: 1st August 2010 - 31st July 2013 and 2. Subsample: 1st August 2013- 31st July 2016) findings suggest that Bitcoin returns are random in the second subsample. Informational efficiency of the Bitcoin market particularly the time varying behavior of long memory of returns on Bitcoin and volatility from 2011 to 2017 has been analyzed by Bariviera (2017) using the Hurst exponent. It is found in the study that daily returns suffered a regime switch. From 2011 until 2014 the returns' time series was essentially persistent whereas after that year, the behavior seems to be compatible with a white noise. On the other hand, daily volatility (measured as the logarithmic difference between daily maximum and minimum price) exhibits a persistent behavior during all the period. In addition, the long memory content of daily volatility is stronger than in daily returns according to the results.

The liquidity and market efficiency has been examined by Wei (2018) for 456 different cryptocurrencies, and results of the study reveal that return predictability diminishes in cryptocurrencies with high market liquidity. Moreover, whilst Bitcoin returns are showing signs of efficiency, numerous cryptocurrencies still exhibit signs of autocorrelation and non-independence.

Wei (2018) also argues that higher transaction costs in the markets where turnover is low impacts the ability for traders to act quickly and readily, resulting in market inefficiency. As a result, findings suggest that whilst established cryptocurrencies are improving in terms of market efficiency, new altcoins with limited liquidity continue to struggle. Brauneis and Mestel (2018) also analyzed the efficiency of cryptocurrency market by using the data of 73 cryptocurrencies ranging from 08/31/2015 to 11/30/2017 and matching the criteria for a market capitalization of at least USD 1 million. Their findings are corroborating Urquhart's (2016) results that Bitcoin is the least predictable (i.e. most 'efficient') cryptocurrency and efficiency exhibits a heterogeneous pattern, probably related to liquidity and size. According to Brauneis and Mestel (2018) turnover ratio proxies for the measure of liquidity and positively affect efficiency and market capitalization proxies for size and it also affect efficiency positively.

Vidal-Tomás and Ibanez (2018) examined semi-strong efficiency of Bitcoin in the Bitstamp and Mt.Gox markets, showing how the digital currency responds to monetary policy and Bitcoin events. The data that has been used for the study is sourced from the Bitstamp and Mt.Gox markets from 13 September 2011 to 17 December 2017, and from 13 September 2011 to 25 February 2014, respectively. According to results, Bitcoin is semi-strong form inefficient in the case of monetary policy news since the digital currency is not responding to this kind of news. On the other hand, Bitcoin responds to negative events in the Bitstamp and Mt.Gox markets while it only responds to positive news in the Bitstamp market. In other words, Bitcoin responds to its own events, but not because of international monetary policy news. Vidal-Tomás et al., (2019) analyzed the existence of herding in the cryptocurrency market through the cross-sectional standard (absolute) deviation of returns. The main findings show that extreme dispersion of returns is explained by rational asset pricing models although it is possible to observe herding during down markets, which highlights the inefficiency and risk of cryptocurrencies. Results also imply that the smallest digital currencies are herding with the largest ones, thus traders base their decisions on the performance of the main cryptocurrencies.

Recently, investigators have also examined the effects of herding behavior in the cryptocurrency market. Bouri et al. (2018) examined herding behavior by using the daily data of the 14 leading cryptocurrencies and employing logistic regression, found that herding occurs as uncertainty increases and it varies over time. Another study by Ajaz and Kumar (2018) revealed that for the 6 major cryptocurrencies, herding is dependent upon market activity rather than market volatility. Baur and Dimpfl (2018) investigated 20 of the largest cryptocurrencies and the results suggested that cryptocurrency volatility generally increases after positive shocks. Moreover, the behavior of informed and noise traders explains that the reaction and fear of missing out is particularly prominent for cryptocurrencies. However, in the present study, the increased volatility in response to positive shocks is explained with uninformed investors' herding, this inference is not based on a herding measure such as the CSAD methodology.

da Gama Silva et al., (2019) analyzed herding behavior and contagion phenomena in the cryptocurrency market by selecting 50 of the most liquid and capitalized currencies. By using the

CSSD and CSAD tests, the results revealed herding behavior, demonstrating extreme periods of adverse herd behavior. Ballis and Drakos (2019) explored whether herding behavior exists in the cryptocurrency market by using the data of 6 major currencies. Based on the CSSD and CSAD methodology, the findings suggest that investors in the “top” sector of the cryptocurrency market act irrationally and imitate other's decisions with no reference to their own beliefs. Thus, cryptocurrencies show a behavior where they tend to move in tandem and it does not necessarily reflect their fundamentals. Haryanto et al., (2019) tested the existence of herding behavior in Bitcoin market by using two dispersion models CSSD and CSAD methodology. The dataset used in the study contains about 21.2 million individual trade records of about 127k unique trader ID's obtained from Mt.Gox and dated from Apr 1, 2011 to Nov 30, 2013. Although CSSD test results did not detect any herding, according to the results of the CSAD methodology, measurement against different market conditions shows that herding moves along with market trend (in the bullish market a positive market return increases herding, while in the bearish market a negative market return increases herding). Findings also show that a low trading volume increases herding behavior, which is different from the results of the study on the stock market (Demirer and Kutan 2006). Moreover, when measured against weekly interval data, herding becomes weaker and less consistent. Another recent study by Kaiser and Stöckl (2019) involved all coins available at every point in time. They contributed to the existing literature on herding in cryptocurrencies by taking into account bitcoin as ‘transfer currency’ and beta herding as an additional measure. They reported that they found strong evidence of herding in contrast to the findings of Vidal-Tomás et al. (2019).

Along with the empirical studies on herding behavior there are also several studies which focus on the social media and internet nexus cryptocurrency prices. Hence there is no fundamental value of cryptocurrencies and macroeconomic fundamentals to shed light on the expected future prices or a fair price, investors’ sentiment becomes a crucial variable and investors’ faith in the perpetual growth becomes an important determinant of the prices (Kristoufek, 2013). The dynamic relationship between the BitCoin price and the interest in the currency measured by search queries on Google Trends and frequency of visits on the Wikipedia page on BitCoin has been analyzed by Kristoufek (2013). Findings reveal that there is a very strong correlation between price level of the digital currency and both the Internet engines, moreover, a strong causal relationship between the prices and searched terms. Interestingly, this relationship is bidirectional, i.e. not only do the search queries influence the prices but also the prices influence the search queries based on the results. Another important implication of the study suggests that as an indicator of a bubble behavior, while the prices are high (above trend), the increasing interest pushes the prices further atop. On the other hand, if the prices are below their trend, the growing interest pushes the prices even deeper. This forms an environment suitable for a quite frequent emergence of a bubble behavior which indeed has been observed for the Bitcoin (Kristoufek, 2013). A recent paper by Shen et al., (2019) have dealt with the link between investor attention and Bitcoin returns, trading volume and realized volatility by employing the number of tweets from Twitter as a measure of attention rather than Google trends. According to Shen et al., (2019) this is a better measure to analyze the behavior of more informed investors. Empirical findings of the study imply that the number of tweets is a

significant driver of next day trading volume and realized volatility which is supported by linear and nonlinear Granger causality tests.

Most studies in the field of herd behavior have only focused on CSSD and CSAD methodology despite this, very few studies have investigated the effect of different volatility regimes. Relevant studies analyzed different markets such as commodity markets, stock markets, REITs and oil markets (see; e.g., Balcilar and Demirer, 2015; Babalos et al., 2015; Demirer et al., 2015; Balcilar et al., 2014). However, previous studies of herd behavior have not dealt with the effect of different volatility regimes and uncertainty on the herd behavior in the cryptocurrency markets. Therefore, we examined the effects of both low and high volatility regimes on herding under uncertainty. As Baur and Dimpfl (2018) found evidence for the presence of noise traders in the cryptocurrency market (also see Kristoufek, 2013; Fry and Cheah, 2016), uninformed investors tend to rely on the behavior of crowd where they are less confident in their own information and cannot interpret the market signals truly enough. Baur and Dimpfl (2018) also suggested that positive shocks increase the volatility by more than negative shocks therefore herding behavior may differ between low and high volatility regimes. Moreover, economic policy uncertainty of U.S. (EPU) has a predictive power on Bitcoin returns according to Demir et al., (2018). Bitcoin returns are negatively associated with the EPU however, the effect is positive and significant at both lower and higher quantiles of Bitcoin returns and the EPU (Demir et al., 2018). The findings of Cheng and Yen (2019) implies that EPU index of China predicts bitcoin returns, but the U.S., Japan, and Korea EPU indexes have no such ability. Because of a lack of regulation in cryptocurrency market the investors are generally afflicted with some uncertainty. Corbet et al., (2017) investigated the relationship between four central banks' (US; FOMC, UK; BOE, EU; ECB, Japan; BOJ) monetary policy announcements and Bitcoin returns. Based on the findings of Corbet et al., (2017), quantitative easing decisions are found to have generated the most significant influence. FOMC interest rate increases led to a significantly positive increase in bitcoin volatility, while reductions in ECB and BOJ interest rates corresponded with reduced levels of bitcoin volatility. All QE announcements made by the four central banks had a strong significantly positive effect on bitcoin returns volatility (Corbet et al., 2017) Hence, the results on the relationship between economic policy and cryptocurrencies are mixed, by utilizing time varying Markov-switching model (TV-MS) we tested the dynamic relationship between economic policy uncertainty (proxied by EPU of U.S.) and herding in low and high volatility regimes. We also used dummy variables to investigate whether or not an asymmetric behavior occurred during the "up and down" market periods.

3. DATA AND MODELLING STRATEGY

3.1. Data Construction

We use daily data of the 14 leading crypto-currencies² that constitute 78% of total cryptocurrency's market capitalization, in terms of closing price, market cap and transaction

² The selected crypto-currencies are; Bitcoin, Ethereum, Ripple, Litecoin, Stellar, Dash, Nem, Monero, Bytecoin, Verge, Siacoin, BitShares, Decred and Dogecoin.

volume as provided by coinmarketcap.com. We also utilized the Daily News Index of the United States as a proxy of economic policy uncertainty as provided by policyuncertainty.com. The starting date for data collection was 28 April 2013 only for Bitcoin and Litecoin; for others the starting date varied due to differences in the initial coin offering and the closing date was the same for all variables as 14 November 2018 (see Appendix B).

3.2. Empirical Framework

3.2.1. CSAD Calculation Method

In terms of a herding measure, Christie and Huang (1995) measure return dispersion and use two dummy variables to capture the dispersion using cross-sectional standard deviation (CSSD) during the market periods, especially in the extreme market movement. Chang et al. (2000) proposed a further developed measure of return dispersion called cross-sectional absolute deviation (CSAD) (Chen et al., 2017). In this study, following Chang et al. (2000), we used the CSAD methodology among individual returns within cryptocurrencies to identify the non-linear relationship between the level of cryptocurrency return dispersions and the overall market return. The CSAD statistic was formulated as shown below:

$$CSAD_t = \sqrt{\frac{\sum_{i=1}^N (r_{i,t} - r_{m,t})^2}{N-1}} \quad (1)$$

where $R_{i,t}$ and $R_{m,t}$ is the return on crypto-currency i and the equal weighted average return of all crypto-currencies in the portfolio for day t , respectively, and n is the number of crypto-currencies in the portfolio. Herding behavior assumes that individual investors make investment decisions following the collective actions of the market, and that these actions will lead security returns to converge with the overall market return. Therefore, herding behavior implies that security dispersions (i.e. $CSAD_t$) will decrease with the absolute value of the market return, since each asset becomes similar with regard to sensitivity to the market return (Akinsomi et al., 2018).

Chang et al. (2000) suggested that during periods of market stress, one would expect return dispersion (i.e. $CSAD_t$) and market return (i.e. $R_{m,t}$) to have a nonlinear relationship. Christie and Huang (1995) argued that the probability of herd behavior increases during periods of extreme market returns and large price movements; therefore, we have a benchmark model based on the following quadratic model of return dispersion and market return:

$$CSAD_t = \alpha_0 + \alpha_1 |R_{m,t}| + \alpha_2 R_{m,t}^2 + \varepsilon_t \quad (2)$$

The presence of herding is tested through the following hypotheses:

H₀: In the absence of herding behavior, we expect in Eq (2) that $\alpha_1 > 0$ and $\alpha_2 = 0$.

H₁₁: If herding behavior exists, we expect $\alpha_2 < 0$.

H₁₂: If anti-herding behavior exists, we expect $\alpha_2 > 0$.

A negative and statistically significant α_2 coefficient provides evidence of herding behavior, i.e. the cross-sectional dispersion of returns increases (if α_1 coefficient is positive and statistically significant) but at a decreasing rate. This is enough to document herding behavior (Economou et al., 2018). It is argued in Economou et al., (2018) that herding may display an asymmetric behavior during up and down market periods. It has been clarified in Economou et al., (2015) that down-markets may lead to herding as they actuate investors to unload their positions in order to avoid suffering further losses in case the downturn becomes prolonged. On the other hand, up-markets can also motivate herding, since they can lead investors to ride on what they believe to be an upward trend (De Long et al., 1990; cited in Economou et al., 2015). Based on several studies (i.e. Chiang and Zheng, 2010; Chiang et al., 2010; Economou, et al., 2011 and Economou et al., 2018 among others) we reestimated our regression including dummy variables for up and down market periods as following:

$$CSAD_t = \alpha_0 + \alpha_1 D^{up} |R_{mt}| + \alpha_2 (1 - D^{up}) |R_{mt}| + \alpha_3 D^{up} R_{mt}^2 + \alpha_4 (1 - D^{up}) R_{mt}^2 + \varepsilon_t \quad (3)$$

where D^{up} is a dummy variable that takes the value 1 on days with positive market returns and the value 0 otherwise.

3.2.2. Time Varying Markov-Switching Model

Hamilton (1989) developed a Markov regime shift model by using post-war gross national product (GNP) data of United States (US), in order to analyze the transitions between expansion and recession periods of business cycles. This study is the most popular in the literature that applies Markov regime shift model (Chen, 2006; Hansen, 1992) and Hamilton's well-known business cycle classification has been adopted in numerous other applications (Bazzi et al., 2016). The study of Goldfeld and Quandt (1973) is the first attempt to extend the regime shift model and they employed the model for exchange rate series. In the study, regime shift model is expressed as below:

$$Y_t = \ln \left[\frac{E_t}{E_{t-1}} \right] \quad (4)$$

where E_t represents the parity. We employed a benchmark model based on the two-state Markov regime shift model developed by Hamilton (1989) and Hansen (1992). A standard Markov switching (MS) model with two regimes can be written as:

$$e_t = \mu_{st} + \sigma_{st} \varepsilon_t \quad \varepsilon_t \sim N(0,1) \quad (5)$$

or:

$$e_t = \begin{cases} \mu_1 + \sigma_1 \varepsilon_t & , \quad S_t = 0 \\ \mu_2 + \sigma_2 \varepsilon_t & , \quad S_t = 1 \end{cases} \quad (6)$$

where, ε_t ; represents the white noise error term, μ ; sample mean, σ ; error term variance. $S_t=0$ and $S_t=1$, denotes the unobserved state of the system. It is assumed that transition between states is governed by a first-order Markov process (Hamilton, 1989):

$$\begin{aligned} \Pr [S_t = 0 | S_{t-1} = 0] &= p, \\ \Pr [S_t = 1 | S_{t-1} = 0] &= 1 - p, \\ \Pr [S_t = 1 | S_{t-1} = 1] &= q, \\ \Pr [S_t = 0 | S_{t-1} = 1] &= 1 - q \end{aligned} \quad (7)$$

Diebold et al. (1994) and Filardo (1994) showed in separate studies that the assumption of a constant transition probability matrix for a MS model is too restrictive for many empirical applications. They extended the standard MS model to allow for transition probabilities that vary over time using observable covariates, including strictly exogenous explanatory variables and lagged values of the dependent variable (Bazzi et al., 2016).

Figure 1. Transition Probabilities Matrix

		Time t	
		State 0	State 1
State 0	Time $t-1$	p_t^{00}	$p_t^{01} = (1 - p_t^{00})$
		$P(s_t = 0 s_{t-1} = 0, x_{t-1}; \beta_0)$	$P(s_t = 1 s_{t-1} = 0, x_{t-1}; \beta_0)$
State 1		$\frac{\exp(x'_{t-1} \beta_0)}{1 + \exp(x'_{t-1} \beta_0)}$	$1 - \frac{\exp(x'_{t-1} \beta_0)}{1 + \exp(x'_{t-1} \beta_0)}$
		$p_t^{10} = (1 - p_t^{11})$	p_t^{11}
State 1		$P(s_t = 0 s_{t-1} = 1, x_{t-1}; \beta_1)$	$P(s_t = 1 s_{t-1} = 1, x_{t-1}; \beta_1)$
		$1 - \frac{\exp(x'_{t-1} \beta_1)}{1 + \exp(x'_{t-1} \beta_1)}$	$\frac{\exp(x'_{t-1} \beta_1)}{1 + \exp(x'_{t-1} \beta_1)}$

Note: $x_{t-1} = (1, x_{1,t-1}, \dots, x_{(k-1),t-1})$ and $\beta_i = (\beta_{i0}, \beta_{i1}, \dots, \beta_{i(k-1)})$, $i = 0, 1$. (Diebold et al., 1994)

The time-varying Markov-switching (TV-MS) model with two states is illustrated in figure 1. In the figure, $\{S_t\}_{t=1}^T$ denotes the sample path of a first-order, β_i : denotes transition probability parameter vectors and two transition probabilities are time varying, evolving as logistic functions of $x'_{t-1} \beta_i$, $i = 0, 1$, where the $(k \times 1)$ conditioning vector x_{t-1} contains economic variables that affect the state transition probabilities (Diebold et al., 1994). The main advantage of the TV-MS model against the constant transition probability specification is that it allows the duration of herd behavior to vary across different regimes of market volatility (Akinsomi et al., 2018). It also allows determination of the effect of economic policy uncertainty and market sentiment, as measured by the US Daily News Index (EPU). We can write the regression we estimated by taking the role of uncertainty into consideration as shown below:

$$CSAD_t = \alpha_{0,S_t} + \alpha_{1,S_t} |R_{mt}| + \alpha_{2,S_t} R_{mt}^2 + \alpha_3 EPU_t + \varepsilon_t \quad (8)$$

where, S_t is a discrete regime variable taking values $\{0, 1\}$ in a two-state Markov-process. Therefore, after modelling the role of EPU, we can define the transition probabilities of the Markov chain in Equation (8) as follows:

$$p_{ij,t} = P(S_t = i | S_{t-1} = j, \mathbf{Z}_{t-1}) \quad (9)$$

where $\mathbf{Z}_t$ is a vector of exogenous EPU variables. Following the approach in Economou et al. (2018), we tested the asymmetric herding behavior³ as well as the structural breaks of the series by utilizing Quandt-Andrews breakpoint test and Bai-Perron (2003) multiple breakpoint test, in order to determine the sub-periods for the TV-MS model.

4. EMPIRICAL FINDINGS and DISCUSSION

To identify the herding behavior, we first estimated the static model with ordinary least squares (OLS) test and the results can be seen in table 1. According to the results, the values of α_1 and α_2 are greater than zero (positive) and statistically significant. This implies that there was an anti-herding behavior in the cryptocurrency markets during the observation period. Table 2 represents the results of the GARCH (1, 1) model. The coefficients α_1 and α_2 are positive and statistically significant which implies an anti-herding behavior and this result confirms previous OLS outputs.

Table 1. Test Results of OLS

Parameter	Coefficient	Std. Error	t-Statistic
α_0	0.039862	0.00112	35.60291*
α_1	0.091596	0.042306	2.165068**
α_2	0.716654	0.222117	3.226479*
Adj. R^2	Log L	AIC	
0.716654	3109.895	-4.29129	

Notes: R^2 denotes the adjusted coefficient of determination, log L denotes the log likelihood of the OLS model and AIC denotes the Akaike information criterion. *, ** represent significance at the 1% and 5% levels, respectively. Newey-West Standard Errors have been considered.

Table 2. Results of the GARCH (1, 1) Model

Parameter	Coefficient	Std. Error	t-Statistic	Prob.
α_0	0.037371	0.003201	11.67386	0.0000
α_1	0.017817	0.036443	0.488912	0.6249
α_2	0.676772	0.234396	2.887306	0.0039
EPU	0.000175	0.00076	0.230632	0.8176
Variance Equation				
C	3.27E-05	4.80E-06	6.826913	0.0000

³It has been argued in Economou et al. (2018) that herding may display an asymmetric behavior during "up and down" market periods. Based on several studies (i.e. Chiang and Zheng, 2010; Chiang et al., 2010; Economou et al., 2011 and Economou et al., 2018 among others) we re-estimated our regression including dummy variables for "up and down" market periods as follows:

$$CSAD_t = \alpha_0 + \alpha_1 D^{up} |R_{mt}| + \alpha_2 (1 - D^{up}) |R_{mt}| + \alpha_3 D^{up} R_{mt}^2 + \alpha_4 (1 - D^{up}) R_{mt}^2 + \varepsilon_t \quad (8)$$

where D^{up} is a dummy variable that takes the value 1 on days with positive market returns and the value 0 otherwise. However, we test whether or not herding/anti-herding display an asymmetric behavior for both overall sample and sub-periods, the coefficients of dummies are statistically insignificant in all cases.

RESID(-1)²	0.153009	0.017112	8.941538	0.0000
GARCH(-1)	0.808678	0.015665	51.62167	0.0000
Adj. R²	RSS	Log L	AIC	
0.04432	1.190161	3318.027	-4.57324	

Notes: Adj. R² denotes the adjusted coefficient of determination, RSS denotes the residual sum of squares, log L denotes the log likelihood of the GARCH model and AIC denotes the Akaike information criterion.

The results of the TV-MS model for the overall sample are presented in table 3. Regime 1 is defined as a low volatile regime and regime 2 is defined as a high volatile and risky regime. A positive sign for α_2 implies an anti-herding behavior while a negative sign implies that a herding behavior exists. In regime 1, α_1 and α_2 are statistically insignificant. In regime 2, α_1 and α_2 have negative and positive signs respectively which indicates that there is an anti-herding behavior in the cryptocurrency market during high volatile regime periods. In the low volatility regime (i.e. regime 1), the effect of economic policy uncertainty is statistically significant (0.009731) at 10% significance level (0.0893) however the impact of uncertainty is statistically insignificant for high volatility regime (i.e. regime 2). Moreover, the TV-MS model fits better than the OLS and GARCH models based on the smallest AIC values.

Table 3. Time Varying Markov Switching Test Results (Overall Period)

Parameter	Coefficient	Std. Error	z-Statistic	Prob.	Time-varying transition probabilities			
$\alpha_{0,0}$	0.074887	0.007338	10.20536	0.0000	Mean		1	2
$\alpha_{1,0}$	-0.012533	0.170678	-0.073428	0.9415		1	0.771914	0.228086
$\alpha_{2,0}$	0.950620	1.353125	0.702537	0.4823		2	0.069927	0.930073
LOG(SIGMA)	-3.345957	0.082549	-40.53292	0.0000	Std. Dev.		1	2
$\alpha_{0,1}$	0.034023	0.001470	23.13898	0.0000		1	0.060291	0.060291
$\alpha_{1,1}$	-0.104717	0.038011	-2.754903	0.0059		2	0.006552	0.006552
$\alpha_{2,1}$	1.148603	0.202544	5.670891	0.0000				
LOG(SIGMA)	-4.210506	0.066158	-63.64330	0.0000				
Transition Matrix Parameters					Time-varying expected durations			
P11-C	0.488385	0.565473	0.863675	0.3878	Mean		1	2
P11-EPU	0.009731	0.005727	1.699157	0.0893		1	5.022701	14.40614
P21-C	-2.760987	0.407782	-6.770737	0.0000		2	3.265103	1.144366
P21-EPU	0.002120	0.004099	0.517291	0.6050				
RSS	0.971961	Log L	3493.548	AIC	-4.808768			

Notes: RSS denotes the residual sum of squares, log L denotes the log likelihood of the TV-MS model and AIC denotes the Akaike information criterion. Bold numeric characters imply statistically significant coefficients and their probabilities.

The TV-MS transition probabilities and expected durations of regimes are also given in table 3. The results revealed that the high volatility regime is the most persistent market regime with the longest average regime duration involving 14.4 days. A low volatility regime has an average duration of 5 days. The transition probabilities of regimes and smoothed probability plots for overall sample are given in the figure 2. The results suggest that the low volatility regime (i.e. regime 1) follows the low-volatility regime and high volatility regime (i.e. regime 2) follows high volatility regime. In other words, during periods of extreme market returns and large price movements, the cryptocurrency market is more likely to follow on this risky and high volatility

regime. On the other hand, in the high volatility regime an anti-herding behavior occurs in the market.

Figure 2. Panel A: Transition Probabilities and Panel B: Smoothed Transition Probability. (Overall Sample)

Panel A

Panel B

Notes: Blue and red lines demonstrate the smoothed transition probability of regimes 1 and 2, respectively.

Based on the results of breakpoint tests (Quandt Andrews and Bai-Perron⁴), we re-estimated the TV-MS model for the sub-periods (1st sub-period: 4/29/2013-09/03/2015; 2nd sub-period: 09/05/2015- 2/26/2017; 3rd sub-period: 2/28/2017- 1/15/2018; 4th sub-period: 1/17/2018- 11/15/2018) which are represented in Table 4. The findings suggest that it is only in the 3rd sub-period in the low volatility regime (regime 1), that there is a herding behavior in the cryptocurrency market and in the high volatility regime (i.e. regime 2) there is an anti-herding behavior which is led by economic policy uncertainty at 10% significance level. The effect of uncertainty is statistically insignificant in the 1st, 2nd and 4th sub-periods. For the 1st sub-period, results imply an anti-herding behavior in both low and high volatility regimes. All coefficients for 2nd sub-period are found to be statistically insignificant. For the 4th sub-period, results indicate an anti-herding behavior only in the low volatility regime.

Table 4. TV-MS Results of Sub-Periods

(Panel A. 1st sub-period) (4/29/2013- 09/03/2015)					(Panel B. 2nd sub-period) (09/05/2015- 2/26/2017)				
Parameter	Coeff.	Std. Err.	z-Stat.	Prob.	Parameter	Coeff.	Std. Err.	z-Stat.	Prob.
$\alpha_{0,0}$	0.03125	0.001152	27.1374	0.0000	$\alpha_{0,0}$	0.035146	0.001532	22.94751	0.0000
$\alpha_{1,0}$	-0.14015	0.044643	-3.13949	0.0017	$\alpha_{1,0}$	0.077117	0.188582	0.408932	0.6826
$\alpha_{2,0}$	1.33824	0.145232	9.21453	0.0000	$\alpha_{2,0}$	-0.64825	1.959544	-0.33082	0.7408
Log(Sigma)	-4.21203	0.050999	-82.5911	0.0000	Log(Sigma)	-4.40752	0.108019	-40.8032	0.0000
$\alpha_{0,1}$	0.08427	0.010026	8.40557	0.0000	$\alpha_{0,1}$	0.06051	0.006839	8.847741	0.0000
$\alpha_{1,1}$	-0.35865	0.252070	-1.42281	0.1548	$\alpha_{1,1}$	0.12947	0.160749	0.805474	0.4205

⁴ The results of the breakpoint tests and the estimation results with dummy variables in order to analyze asymmetric behavior are not reported in the article for the interest of brevity and are available upon request from the authors.

$\alpha_{2,1}$	3.19926	1.129161	2.83331	0.0046	$\alpha_{2,1}$	-0.99588	1.113385	-0.89446	0.3711
Log(Sigma)	-3.17173	0.135753	-23.3640	0.0000	Log(Sigma)	-3.89530	0.077591	-50.2032	0.0000
Transition Matrix Parameters					Transition Matrix Parameters				
P11-C	2.47093	0.387322	6.37952	0.0000	P11-C	2.72822	1.057873	2.57897	0.0099
P11-EPU	-0.00480	0.003843	-1.25119	0.2109	P11-EPU	-0.00192	0.007582	-0.25417	0.7994
P21-C	-0.33076	0.609065	-0.54307	0.5871	P21-C	-1.52722	1.440772	-1.06000	0.2891
P21-EPU	0.00546	0.007601	0.71874	0.4723	P21-EPU	-0.00292	0.013823	-0.21188	0.8322
RSS	0.523624	Log L	1466.988		RSS	0.119459	Log L	1029.594	
AIC	-4.739373				AIC	-5.286203			
(Panel C. 3rd sub-period) (2/28/2017- 1/15/2018)					(Panel D. 4th sub-period) (1/17/2018- 11/15/2018)				
Parameter	Coeff.	Std. Err.	z-Stat.	Prob.	Parameter	Coeff.	Std. Err.	z-Stat.	Prob.
$\alpha_{0,0}$	0.082417	0.007647	10.77836	0.0000	$\alpha_{0,0}$	0.016260	0.001535	10.59116	0.0000
$\alpha_{1,0}$	0.584218	0.234526	2.491060	0.0127	$\alpha_{1,0}$	0.141841	0.067954	2.087304	0.0369
$\alpha_{2,0}$	-2.690646	1.394036	-1.93011	0.0536	$\alpha_{2,0}$	1.003378	0.372401	2.694351	0.0071
Log(Sigma)	-3.527069	0.063595	-55.4611	0.0000	Log(Sigma)	-5.07621	0.095302	-53.2644	0.0000
$\alpha_{0,1}$	0.052767	0.002595	20.33594	0.0000	$\alpha_{0,1}$	0.041213	0.002860	14.40980	0.0000
$\alpha_{1,1}$	-0.224199	0.093091	-2.40840	0.0160	$\alpha_{1,1}$	0.070854	0.175255	0.404288	0.6860
$\alpha_{2,1}$	1.317398	0.501456	2.627147	0.0086	$\alpha_{2,1}$	-1.16890	1.573696	-0.74277	0.4576
Log(Sigma)	-4.061795	0.064693	-62.7855	0.0000	Log(Sigma)	-4.08022	0.165310	-24.6822	0.0000
Transition Matrix Parameters					Transition Matrix Parameters				
P11-C	2.625093	1.709549	1.535547	0.1246	P11-C	2.486005	0.929047	2.675866	0.0075
P11-EPU	-0.00123	0.014532	-0.08472	0.9325	P11-EPU	-0.00899	0.009492	-0.94750	0.3434
P21-C	-4.47352	1.228880	-3.64032	0.0003	P21-C	-2.18204	0.590726	-3.69383	0.0002
P21-EPU	0.014874	0.009034	1.646568	0.0996	P21-EPU	0.004164	0.006602	0.630691	0.5282
RSS	0.168107	Log L	534.1564		RSS	0.048605	Log L	627.7198	
AIC	-4.520835				AIC	-5.701109			

Notes: RSS denotes the residual sum of squares, log L denotes the log likelihood of the TV-MS model and AIC denotes the Akaike information criterion. Bold characters imply the statistically significant coefficients and their probabilities.

The transition probabilities and expected durations for sub-periods are given in table 5. The results of transition probabilities are consistent with the results given in figure 3. Results for all sub-periods implied that the high volatility regime is the most persistent market regime and the longest average regime duration is 17.53 days in the 3rd sub-period. In the 1st sub-period, a low volatility regime has an average duration of 1.77 days and a high volatility regime has an average duration of 8.06 days. In the 2nd sub-period, a low volatility regime has an average duration of 7.53 days and a high volatility regime has an average duration of 13.15 days. Finally, in the 4th sub-period, the duration for low volatility regime is 7.88 days and the duration for high volatility regime is 7.85 days.

Table 5. Time-Varying Transition Probabilities and Expected Durations

(Panel A. 1st sub-period) (4/29/2013- 09/03/2015)			(Panel B. 2nd sub-period) (09/05/2015- 2/26/2017)		
Time-varying transition probabilities			Time-varying transition probabilities		
	1	2		1	2
1	0.4365	0.5634	1	0.8673	0.1326
2	0.1239	0.8760	2	0.0760	0.9239
Time-varying expected durations			Time-varying expected durations		
Regime 1	1.77		Regime 1	7.53	
Regime 2	8.06		Regime 2	13.15	
(Panel C. 3rd sub-period) (2/28/2017- 1/15/2018)			(Panel D. 4th sub-period) (1/17/2018- 11/15/2018)		

Time-varying transition probabilities			Time-varying transition probabilities		
	1	2		1	2
1	0.9233	0.0766	1	0.8732	0.1267
2	0.0570	0.9429	2	0.1273	0.8726
Time-varying expected durations			Time-varying expected durations		
Regime 1	13.03		Regime 1	7.88	
Regime 2	17.53		Regime 2	7.85	

High volatility means higher risk and higher risk enables a part of some investors to get higher returns. In a volatile environment the winner wins more and the loser losses more relatively to normal periods. Winners may become overconfident based on the high returns because of the self-serving bias (Shtudiner et al., 2017) or house money effect (Thaler and Johnson, 1990) and overconfident investors trade excessively according to Barber and Odean (2001). On the other hand, losers may also trade excessively by the reason of compensation of losses or break-even effects (Kahneman and Tversky 1979; Thaler and Johnson, 1990). The reason behind the longer durations of high volatility regime compare to low volatility regime may be two kind of investors: overconfident ones who trade excessively because of house money effect and losers who prefers to compensate her losses because of break-even effect rather than being risk-averse because of a snake bite effect. By reason of either overconfidents or losers, trading volume increases in the high volatility regimes and this kind of aggressive investing strategies may cause such periods entail longer.

The transition probabilities of regimes and smoothed probability plots for sub-periods are given in the figure 3 and figure 4 respectively. For all sub-periods, the results imply that in the low volatility regime (i.e. regime 1) market is more likely to stay in the low-volatility regime and in the high volatility regime market is more likely to pursue this risky and high volatility regime (i.e. regime 2). The probability of a transition from regime 1 to regime 2 is low for all sub-periods. Smoothed transition probabilities which are represented in figure 4, demonstrate that 1st sub-period is the most volatile period (also see table 5). As the blue and red lines demonstrate the smoothed transition probability of regime 1 (low volatility) and regime 2 (high volatility) respectively, the probability of high volatility regime is higher than the low volatility regime in the 3rd sub-period where herding is observed during low volatility regime.

Figure 3. Transition Probabilities for Sub-Periods. Panel A: 1st Sub-Period. Panel B: 2nd Sub-Period. Panel C: 3rd Sub-Period. Panel D: 4th Sub-Period

Panel A

Panel B

Panel C

Panel D

Figure 4. Smoothed Transition Probabilities for Sub-Periods

Note: Blue and red lines demonstrate the smoothed transition probability of regimes 1 and 2, respectively.

When we analysed the price of Bitcoin, (figure 5) we observed a remarkable rise in closing price since February/2017 and it reached its highest level at the following date: 12/17/2017, followed by a sharp drop. It fell to the lowest level at the date: 02/05/2018 before a price rally. This large price movement period mostly corresponds to the 3rd sub-period in our analysis. In this period, we observed an anti-herding behavior during the high volatility regime. However, during a low volatility regime (i.e. regime 1), the effect of herding appeared to be stronger in the cryptocurrency market which may indicate that Bitcoin dominates the entire market. Holmes et al., (2013) states that intentional herding might be expected to be more evident when volatility is low. Thus, if herding is intentional then we expect a relationship to exist between the level of herding and the level of market volatility, although the nature of the association is ambiguous according to Holmes et al., (2013). Moreover, low volatility may be due to positive autocorrelations (Cutler et al., 1990). In the 3rd sub-period, the rise of bitcoin price is consistent hence this tendency may have led the investors to expect the future price to continue rising. In the 3rd sub-period, the price rally phase

corresponds to low volatility as it can be seen from appendix A. This means that the standard deviation of price change is low while the price is high and consistently rising. In brief, our results imply that in the 3rd sub-period volatility decreases while the price rises remarkably and in the low volatility regime investors tend to herd and this behavior may be related with the intentional herding. Our finding is consistent with the study of Vidal-Tomas et al., (2019). As it was argued in Christie and Huang (1995), Babalos and Stavroyiannis (2015) and Goodfellow et al. (2009) among others, investors are more likely to doubt their knowledge during market stress, hence herding becomes more prevalent during such periods. Market stress can be seen in also low volatility regime while the price is consistently rising. Investors may worry about the peak price, in other words, the right price to sell for maximization of the returns. During this period noise trader may have been intentionally herded for buying Bitcoin based on the future price expectations of the market. Our results are consistent with the findings of Haryanto et al., (2019) which claims that in the bullish market a positive market return increases herding. During the 3rd sub-period, the herding behavior may be a reasonable explanation of the crash of Bitcoin. Only in this period low volatility corresponds to a price rally phase different from the other low volatility regimes in other sub-periods. As it can be seen from the appendix A, in other sub-periods price change is relatively low.

Figure 5. The Price of All Cryptocurrencies

In the 3rd sub-period during the high volatility regime, the TV-MS results imply an anti-herding behavior which may be accounted for by the investors' overconfidence in a soaring yield spreads environment. This result is consistent with the findings of Stavroyiannis and Babalos (2017). Based on the results, anti-herding increases with increasing economic policy uncertainty. As suggested by Goodfellow et al. (2009), the higher the degree of overconfidence, the less likely investors are to rely on the behavior of others rather than their beliefs when making investment decisions. Investors that have recently experienced large positive returns in their portfolios appear to be more likely to ignore market signals and over-estimate their ability to make the right investment decision. Under uncertainty and in a high volatility regime, investors tend to rely on their own beliefs based on the positive past returns (in relation to the large price movement of Bitcoin) which may also

infer a positive feedback trading behavior. For the 1st sub-period in both low and high volatility regimes and for the 4th sub-period in a low volatility regime, the results of the TV-MS model indicate an anti-herding behavior which may be related with the investors' overconfidence in the same manner. The findings of Cheng and Yen (2019) implies that the EPU index of U.S. has no ability to predict the price of Bitcoin while EPU index of China does since the largest Bitcoin mining pools are based in China. Also Vidal-Tomás and Ibanez (2018) states that Bitcoin is not affected by monetary policy news, highlighting the absence of any kind of control on Bitcoin. In our study the EPU index of U.S. is significant only in 3rd sub-period during high volatility regime.

5. CONCLUSION

In this paper, we investigated the existence of herding behavior in the cryptocurrencies under uncertainty in different volatility regimes. Our study contributes to the literature on the importance of uncertainty in financial markets and the irrational herding behavior by utilizing time-varying Markov-switching (TV-MS) model to better analyze the effect of different volatility regimes on investor's behavior. To empirically test for herding behavior, we employed cross sectional absolute deviation (CSAD) methodology proposed by Chang et al. (2000). We first tested our regression with OLS and GARCH. Thereafter, we utilized TV-MS model for both overall sample and sub-periods which is determined based on the results of Quandt-Andrews and Bai-Perron structural breakpoint tests. We also used dummy variables to capture an asymmetric behavior of investors during up and down market periods. Table 6 illustrates a summary of our overall results.

Table 6. Summary of the Results

	Regimes	Overall Period	1st Sub-Period	2nd Sub-Period	3rd Sub-Period	4th Sub-Period
R1	Dominant Behavior	Insignificant	Anti-Herding	Insignificant	Herding	Anti-Herding
	Significance of EPU	Significant	Insignificant	Insignificant	Insignificant	Insignificant
R2	Dominant Behavior	Anti-Herding	Anti-Herding	Insignificant	Anti-Herding*	Insignificant
	Significance of EPU	Insignificant	Insignificant	Insignificant	Significant	Insignificant

Notes: * represents the significant uncertainty effect on the herding/anti-herding behavior. R1 indicates Regime 1 (Low Volatility) and R2 indicates Regime 2 (High Volatility).

Based on the results of TV-MS model, for overall sample, market shows an anti-herding behavior. According to sub-period results, in the 1st sub-period there is an anti-herding behavior in the high volatility regime however uncertainty effect is insignificant. In the 2nd sub-period all coefficients are found to be insignificant. In the 3rd sub-period, there is a herding behavior in the low volatility regime and there is an anti-herding behavior in the high volatility regime. Moreover, the effect of uncertainty is significant for high volatility regime. In the 4th sub-period there is an anti-herding behavior in the low volatility regime and the effect of uncertainty is not significant. The large price movement in the price of Bitcoin corresponds to 3rd sub-period in our analysis.

Based on our results, the herding behavior which is observed in the low volatility regime may have led to a price bubble and crash in the relevant period. Our findings may imply that investors are more likely to rely on other investors' information rather than their own information in a low volatile environment. However, in relation with overconfidence, investors may over-estimate their ability in their financial decisions therefore they may ignore the market signals and show an anti-herding behavior under uncertainty. Finally, our results suggested that there was no significant asymmetric behavior during the "up and down" market periods.

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APPENDIX A

Figure 6. Volatility of Bitcoin

APPENDIX B

Figure 7. Initial Offering Dates of Cryptocurrencies

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