Heliyon 6 (2020) e04752

Contents lists available at ScienceDirect

Heliyon

journal homepage: www.cell.com/heliyon

Review article

Herding behaviour in digital currency markets: An integrated survey and empirical estimation

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ARTICLE INFO

Keywords:
Bitcoin
Digital currency
Cryptocurrency
Herding
Survey
Finance
Behavioral economics
International economics
Money
Pricing

ABSTRACT

This paper reviews the empirical literature on the highly popular phenomenon of herding behaviour in the markets of digital currencies. Furthermore, a comparison takes place with outcomes from earlier studies about traditional financial assets. Moreover, we empirically investigate herding behaviour of 240 cryptocurrencies during bull and bear markets. The present survey suggests that empirical findings about whether herding phenomena have made a significant appearance or not in cryptocurrency markets are split. The Cross-sectional absolute deviations (CSAD) and Cross-sectional standard deviations (CSSD) approaches for measuring herding tendencies are found to be the most popular. Different behaviour is detected in bull periods compared to bear markets. Nevertheless, evidence from primary studies indicates that herding is stronger during extreme situations rather than in normal conditions. However, our empirical estimations reveal that herding behaviour is evident only in bull markets. These findings cast light on and provide a roadmap for investment decisions with modern forms of liquidity.

1. Introduction

The worldwide liquidity shortages brought up to the surface by the 2008 Global Financial Crisis have prompted traders, policymakers and academics to focus interest on alternative forms of money and investment assets. The introduction of Bitcoin by Nakamoto (2008) has spurred coin offerings of a wide spectrum of digital currencies that have attracted considerable attention by all types of market participants. Digital currencies constitute alternative forms of liquidity with remarkable differences in ownership, transactions and production matters in relation to the traditional monetary assets (Böhme et al., 2015). A heated debate has aroused concerning whether digital currencies can fulfill the functions of money so be used as means of transactions, store of value and units if account (Yermack, 2015; Ammous, 2018). Their decentralized nature and the lack of regulatory authorities have rendered them widespread since 2017 and extremely popular across speculators but also uninformed investors. The risk-return trade-off through the lens of cryptocurrency volatility has been at the epicenter of academic research (Beneki et al., 2019; Kyriazis et al., 2019). The high level of ignorance about fundamentals of cryptocurrencies has made these markets largely susceptible to collective actions of the market even when these are in sharp contrast to beliefs of individual persons.

Behavioural finance constitutes a sub group of behavioural economics and suggests that pychological factors and biases exert impacts on financial decisions of investors and economic units in general. These influences are at the route of anomalies in markets of financial assets and generate bull or bear phenomena in high speed. "Herding'' in economics and finance stands for the irrational tendency that investors exhibit towards mimicking behaviour of other investors even if they totally disagree with that way of thinking (Spyrou, 2013). This is closely related to irrational exuberance as has been analyzed by Robert Shiller (Shiller, 2015) that leads to over-enthusiasm and the creation of asset price bubbles. Herding behaviour can be expressed in various forms such as trading in the same direction with others, following the trend in previous trades, imitating or correlation one's behaviour to others' behaviour. Usually investors who lack experience are prone to become risk-lovers without being able to understand the risks that they suffer. Such thoughtless behaviour is often encouraged by lack of certainty regarding economic conditions and by extreme conditions in markets, such as during turmoil.

It should be noted that rational herding can also take place. Instead of the case where agents follow other agents blindly –as it happens during irrational herding behaviour-externalities, distortions due to information difficulties or incentive matters can emerge (Devenow and Welch, 1996).

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https://doi.org/10.1016/j.heliyon.2020.e04752
Received 10 February 2020; Received in revised form 8 May 2020; Accepted 17 August 2020
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Rational herding means that investors learn by observing other investors. They use the publicly available information in order to estimate the risk inhibited in the counterparty. Momemtum is less influential when it comes to rational herding decision-making (Zhang and Liu, 2012).

Herding can be divided into a) intentional herding when investors willingly imitate the behaviour of other investors and b) spurious herding when investors have a similar information set that is driven by fundamentals (Galariotis et al., 2016). To be more precise, intentional herding is mainly about imitation triggered by the expectation of some sort of benefit when asymmetric information exists. The belief of being at an informational disadvantage in relation to others leads to herding providing informational payoffs. For this reason, intentional herding results into the creation of informational cascades in order to collect guidance. This type of herding may be inefficient and can be characterized by fragility, extreme fluctuations and systemic risk (Bikhchandani and Sharma, 2001). Moreover, intentional herding brings about professional payoffs concerning fund managers and financial analysts. Their motives of protecting their reputation and preserving their compensation are satisfied through herding during extreme market conditions.

When it comes to spurious (unintentional) herding, this takes place when investors are receivers of common signaling and present hardly different reactions to these signs. Similar investment strategies due to commonality among investment professionals and style investing are at the root of spurious herding. Moreover, home bias appears -leading a lot of investors to prefer home market's stocks-that is reinforced by other psychological factors such as familiarity bias, recognition heuristic and conformity (for more details see: Kallinterakis and Gregoriou, 2017).

Herding has made its appearance in a wide spectrum of alternative financial assets through time and has attracted early attention by high-quality academic studies (Nofsinger and Sias, 1999). To be more precise, herding phenomena have been studied concerning stock markets (Chang et al., 2000; Chiang and Zheng, 2010; Balcilar et al., 2014; Litimi et al., 2016; Bohl et al., 2017), commodities markets (Babalos and Stavroyiannis, 2015; BenMabrouk and Litimi, 2018), bond markets (Galariotis et al., 2016) and mutual funds (Deng et al., 2018). Furthermore, academic work about herding has focused on the house market (Ngene et al., 2017) and REITs (Philippas et al., 2013). Analysis has also been conducted in both microeconomic and macroeconomic levels (Venezia et al., 2011). Moreover, integrated surveys on herding in financial assets have been discussed (Hirshleifer and Hong Teoh, 2003; Belke and Setzer, 2004; Menkhoff et al., 2006; Spyrou, 2013; Kallinterakis and Gregoriou, 2017).

This study focuses on herding behaviour in the digital currency markets as these innovative forms of liquidity are particularly attractive to investors due to their potential for very high profitability. Their fully decentralized character and the encrypted database technology that is called "blockchain'' differentiate them from conventional forms of money and investments as they offer pseudonimity to their users (Böhme et al., 2015). Bitcoin has been the largest-capitalized digital currency during the last decade and herding phenomena in cryptocurrency markets are mainly attributed to its price fluctuations. Up to the present, only the seminal review paper of Corbet et al. (2019) has provided an integrated overview of cryptocurrency characteristics. Moroever, there is a survey paper on the bubble characteristics of cryptocurrencies (Kyriazis et al., 2020) and reviews on the efficiency of cryptocurrency markets (Kyriazis, 2019) and the nexus of Bitcoin with gold (Kyriazis, 2020). Our overview and empirical testing adds to relevant literature by casting light on a specific aspect of behaviour in digital currency markets.

Bitcoin's supply is fixed so the demand for Bitcoin is clearly market-determined. It should be emphasized that despite the hegemonic role of Bitcoin in digital currencies being confirmed, there is also academic work that proves lower-capitalization digital currencies being influential as well as regards herding behaviour. The second largest cryptocurrency in terms of market capitalization has been Ethereum that started trading in August 2015 and constitutes a smart contract. Ethereum presents lower market value so is more accessible to investors but is also in a larger extent prone to protocol alterations by a majority of users. Moreover, Ripple is among the highest capitalized digital currencies. It exhibits a very low market value so is accessible to a larger number of investors. Profit-making by holding Ripple can be achieved due to its large fluctuations in prices. Ripple offers an alternative to conventional financial intermediation practices and is considered to be a trading currency (Ammous, 2018). Furthermore, Litecoin displays high resemblance to Bitcoin and has its supply capped at 84 million coins. It was introduced at July 2012 and has been extremely volatile and attractive to risk-seekers. Special emphasis should be attributed to the Tether stablecoin, which is not mined. It is pegged to and backed by the US dollar (anchored to 1 USD) and has recently become one of the major digital currencies traded. It primarily serves for converting and exchanging into other cryptocurrencies, especially on exchanges not accepting traditional fiat currencies (Wei, 2018).

This integrated survey casts light on rational and irrational investor behaviour and herding phenomena in the markets of digital currencies but also traditional assets. More specifically, the contribution of this paper is threefold. Firstly, understanding of rational and irrational behaviour is enhanced and an overall perspective on herding phenomena in financial markets is provided. Secondly, a comparative analysis of herding behaviour across markets takes place. Thirdly, an empirical estimation of herding is conducted by employing data on a respectable number of cryptocurrencies and comparison takes place between bull and bear periods. This enables the interested reader to have a compass when investing in digital forms of money and investments and better familiarize with the tendency of such markets to follow signals from other cryptocurrency markets, like that of Bitcoin.

In the remainder of this paper, Section 2 provides empirical literature on herding phenomena in a number of categories of traditional financial assets and provides an overview of results. Furthermore, Section 3 lays out the empirical studies investigating herding phenomena in digital currency markets and summarizes findings. In Section 4 the data and methodology employed for the purposes of our empirical estimations are presented. Section 5 provides the empirical analysis concerning herding phenomena in cryptocurrency markets during bull and bear periods and reveals the economic implications. Finally, Section 6 discusses and comments on economic and policy implications and provides the conclusions. Moreover, avenues for future research are suggested.

It should be noted that Table A2 in the Appendix presents in a brief manner the main elements of the studies about herding in cryptocurrency markets and Table A1 displays the digital currencies used in our empirical estimations. Additionally, Figures A1-A3 show some statistical evidence on the references and citations relevant to the studies about herding in cryptocurrency markets.

2. Studies about herding phenomena in traditional financial assets

Academic work on herding behaviour has been based on seminal papers that have provided with in-depth analysis and innovations concerning the measures of herding phenomena. Among them, the studies of Christie and Huang, Hwang and Salmon (2004) and the integrated survey of Spyrou (2013) can be found.

To be more precise, Christie and Huang (1995) investigate herding behaviour by using the cross-sectional standard deviation of returns. They emphasize that herding intensity is low when a lot of investors follow the crowd. On the other hand, rational asset pricing models support that when stocks exhibit different levels of of sensitivity to market movements then higher dispersion arouses. It is argued that during turbulent eras herding expected to be more intense. Despite that, it is revealed that a rational asset pricing model better explains dispersion in such conditions. Moreover, Hwang and Salmon (2004) propose a new approach in order to trace herding behaviour. This method is based on the cross-sectional dispersion of the factor sensitivity of assets in a given market and measures deviation from the equilibrium beliefs as measured

by CAPM prices. This enables them to separate herding from market sentiment and distinguish the latent herding component in asset prices. In contrast to estimations of Christie and Huang (1995), they concentrate interest on the cross-sectional variability of factor sensitivities instead of returns and examine market-wide herding. More specifically, the US, UK, and the Korean markets are under scrutiny, Evidence presents that herding towards the market exhibits significant movements and persistence irrespectively of and given market conditions as is shown in returns and volatility. Herding towards the market portfolio is found during bull and bear markets.

Spyrou (2013) conducts a review about herding phenomena in financial markets at a theoretical or an empirical level. Alternative theories and perspectives about herding as well as measures are presented. The metrics of Lakonishok et al. (1992), Sias (2004), Christie and Huang (1995), Hwang and Salmon (2004) and Chang et al. (2000) are presented. Furthermore, some general conclusions have been reached. Firstly, the empirical evidence does not lead to overall accurate conclusions. Secondly, existing measures of herding have to overcome limitations. Thirdly, empirical tests do not abide by the speed of theoretical advances about herding behaviour of investors. Moreover, further emphasis should be put on the investigation of whether spurious or intentional herding appears. Furthermore, passive herding is not examined by empirical studies. Finally, it is supported that relevant academic work should focus more intensely on herding phenomena in emerging stock markets and institutional investors in these markets. Alternatively, more focus should be made on commodity, derivative and real estate markets.

2.1. Herding phenomena in stock markets

An important number of academic studies have focused on the market of financial assets and irrational behaviour of investors that mimic other investors' actions which is contrary to their own beliefs. A range of influential papers have looked into the nexus between herding and irrational investment decisions and how this has affected profitability and the risk-return trade-off in investor portfolios. In order to acquire the findings by the aforementioned strand of the literature, we dwell on specific papers that are related to herding phenomena in financial markets. This helps us in deriving and analyzing the economic implications and conclusions in latter parts of this survey. The first strand investigated in this survey consists of papers investigating herding behaviour in stock markets.

In their seminal paper, Chang et al. (2000) examine how investors behave in the US and Asian markets. It is revealed that in South Korean and Taiwanese markets significant herding behaviour emerges while a weaker level is detected in Japan. No herding is found in the markets of the US and Hong Kong. Various size-based portfolios confirm these findings. The role of increase in security return dispersion as a function of the aggregate market return presents higher levels during upwards market periods. When it comes to Hirshleifer and Hong Teoh (2003), they provide a literature review and insights on herding behaviour in capital markets. They describe why imitation is interesting in capital markets and emphasis is put on the roots and patterns of convergent behaviour. They support that herding phenomena in equity markets are likely mixtures of reputational impacts, information influences, direct payoff interactions, preference characteristics and imperfect rationality.

Furthermore, Chiang and Zheng (2010) study herding behaviour in 18 countries during the period 1988–2009. Results reveal that herding takes place in advanced equity markets –but not in the US- and in Asian markets whereas no herding is detected in Latin American regions. While herding phenomena are traced both during bull and bear markets, herding asymmetry is found to be more intense in Asian markets during upwards market tendencies. Moreover, contagion effects that influence neighbouring regions are found to take place. By another perspective, Demirer et al. (2010) focus on herding phenomena in the Taiwanese stock market and adopt alternative methodologies in order to understand the sources of herding. Their findings indicate that herding behaviour is more intense during periods of market losses. This leaves no large space for diversification in investors; portfolios during stresses market conditions.

Economou et al. (2011) examine whether countries in Southern Europe have presented herding behaviour during the decade before the outburst of the Global Financial Crisis (GFC). Investigation takes place in relation to market characteristics. They look into whether the cross-sectional dispersion of returns in each market influenced by the dispersion in the other three markets. Moreover, investigation takes place about the impact of the GFC on herding behaviour. Additionally, Holmes et al. (2013) by using cross-sectional regression across all the securities examined provide evidence that institutions in the Portuguese stock market exhibit herding behaviour. This phenomenon is argued to be driven by reputational reasons. Such outcomes offer insights into fund manager behaviour. Moreover, herding is found to be intentional within a concentrated market. When it comes to Lee et al. (2013), they investigate industries in China's A-share markets and support that herding is more intense in some sectors during the bull market. This is more obvious regarding the Shanghai stock market. Moreover, Balcilar et al. (2014) look into the factors that establish the volatility-herding nexus in the emerging equity markets of the oil-rich GCC regions. They investigate the impact of herding on volatility after taking into consideration global factors. A regime-switching smooth-transition regression (STR) model is employed. Evidence indicates that switching from non-herding to herding and the other way around is mainly affected by market volatility. To be more precise, global risk factors are very influential. Contagion is found to take place in financial markets. In their study, Economou et al. (2016) study herding behaviour in the Greek Athens Stock Exchange during the crisis period. By using the cross-sectional dispersion approach, evidence is provided that herding exists under different market conditions. Results from quantile regressions indicate that herding is evident in the upper quantiles of the cross-sectional return dispersion.

Babalos and Stavroyiannis (2015) employ a DCC-GARCH methodology in order to find the connection between anti-herding behaviour and portfolio management. They argue that this behaviour comes up due to different portfolio positioning and rebalancing. More specifically, this phenomenon is more evident with the increase in the short- and long-positioning of the portfolio weights. Generally, it is found that during the financial turmoil no herding takes place and anti-herding behaviour emerges. By a somewhat different point of view, BenSaïda (2017) adopts a modification of the cross-sectional absolute deviation methodology and the GJR-GARCH model to investigate the linkage of herding behaviour with trading volume and investor's sentiment. Evidence indicates that herding takes place in almost every sector of the US stock market during turmoil eras. Such behaviour influences the volatility of a relatively small number of specific stocks while the overall market volatility falls. In a more or less similar vein, Gong and Dai (2017) study whether fluctuations in interest rates and currency values result in herding phenomena in the Chinese stock market. Findings reveal that higher interest rates and lower currency values lead to more intense herding behaviour and this is more evident during bear markets. Additionally, evidence suggests that intentional herding takes place in the Chinese stock market. Surprisingly, Bohl et al. (2017) support that a modification of the herding measure by Chang et al. (2000) can provide clearer evidence of herding behaviour. They test this argument by investigating herding phenomena in the SP500 and the Eurostoxx50 indices.

From their perspective, BenMabrouk and Litimi (2018) study herding behaviour at US industries during extreme oil market movements. By employing a modified version of the cross-section absolute deviation methodology, evidence is provided that no herding takes place in any sector. Furthermore, they support that sectoral herding is more emphasized during downwards movements of the oil market rather than upwards ones. It is further argued that higher volatility in the oil market and more intense fear sentiment weakens herding in US industries. By

adopting their own viewpoint, Deng et al. (2018) look into the herding behaviour of mutual funds during bear periods in stock markets. There is evidence that mutual fund herding is more pronounced during periods of low information disclosure and quality. Furthermore, such herding behaviour is found to fortify the risk of abrupt falls in stock prices. Overall, findings indicate that economic units are more susceptible to exhibit irrational behaviour and lead to herding phenomena during turbulent periods. A number of studies support that during bull markets investors tend to follow the decisions of other investors when it comes to stock trading (Chiang and Zheng, 2010; Lee et al., 2013). On the other hand, there is a larger number of academic papers revealing that during stressed economic conditions herding phenomena become more intense (Demirer et al., 2010; BenSaïda, 2017; Gong and Dai, 2017; Deng et al., 2018). Alternative reasons for the presence of herding behaviour have been detected such as bad information and irrational thinking. The majority of studies agree that market conditions can badly affect rational decision making and distort an investor's beliefs in a large extent and regarding a large spectrum of financial assets.

2.2. Herding phenomena in bond markets and funds by employing micro-data

There is a strand of literature concerning herding phenomena that focuses on bond markets and funds and examination by employing micro-data. Microdata refers to proprietary data on investors' accounts, portfolios and transactions. This sis contrast to studies with aggregate data, such as prices and volume (Kallinterakis and Gregoriou, 2017). It should be noted that Lakonishok et al. (1992), Sias (2004), Borensztein and Gelos (2003), Frey et al. (2014), Galariotis et al. (2016), Cai et al. (2019) and Chen and Ru (2019) constitute relevant academic work.

In their seminal paper, Lakonishok et al. (1992) look into whether herding takes place concerning 769 tax-exempt funds in order to detect their influence on stock prices. Findings reveal that weak evidence of herding exists about smaller stocks and somewhat more powerful evidence of positive-feedback trading. When it comes to larger stocks, small or no levels of herding are derived while also no significant evidence of positive-feedback trading is found. As concerns another very important contribution, Sias (2004) argues that momentum trading that characterizes traders is not a determinant of herding behaviour. It is documented that institutional herding weakens as time passes and does not exhibit the same levels across capitalizations and investor types. Furthermore, it is found that inferring information from institutional investors' trades leads to herding phenomena among these investors.

As concerns the study of Borensztein and Gelos (2003), they reveal that herding phenomena among mutual funds of emerging markets are moderately intensive but are statistically significant. They also support that herding takes place in a larger extent among open-ended funds than among closed-end funds. It is stressed though that herding is not more obvious during crises in comparison with normal conditions. When it comes to Frey et al. (2014), they develop a simple model of trading behaviour and support that it provides an unbiased measure for herding based on investor transactions. They focus on the German market of mutual funds in order to improve the understanding of herding behaviour.

Moreover, Galariotis et al. (2016) investigate for the existence of herding phenomena concerning the European government bond prices. They support that no investor herding took place before or after the crisis in the European Union. Emphasis is put on the finding that macroeconomic news have led to herding behaviour of bond market investors during the crisis. Furthermore, spillover effects of herding are detected. By their own perspective, Cai et al. (2019) provide evidence that institutional herding is more intense in the corporate bond market and especially among speculative-grade bonds. It is also detected that higher probability of herding emerges when selling of mutual funds takes place. Herding is found to lead to asymmetric price impacts. Moreover, the price destabilizing influence of sell herding is revealed to be powerful concerning high-yield bonds, small bonds, bonds of low liquidity levels as well as during the global financial crisis. Regarding Chen and Ru (2019), they employ the simulated method of moment estimator by Chen and Lux (2018) and find that large and small capitalization Chinese stocks exhibit herding phenomena by the perspective of individual investor's behaviour. This is evident especially during the 2015 crash. Additionally, it is argued that before this crash, more powerful herding is detected in large stocks in comparison to smaller ones while during and after the crash the reverse happens.

Overall, it can be argued that herding is not more intense during bear markets in comparison with bull markets though it is more powerful as regards risky and illiquid bonds. Destabilizing and asymmetric impacts of herding are detected on prices. Moreover, open-ended funds are found to be receivers of higher influences from herding behaviour than closed-end funds. Thereby, it can be supported that herding is influential on lower quality bonds which are prone to be employed for the purposes of speculation. Herding is stronger concerning small stocks in extreme conditions –especially bear markets- and that these stocks are in general receivers of higher herding impacts than large stocks. Whatsoever, large stocks are found to exhibit herding behaviour mostly during normal times. Low value stocks are more susceptible to herding phenomena and herding is more popular to risk-takers that seek to exploit profit opportunities and achieve large profits in the short-run. These findings enable interested investors to improve the risk-return trade-off in their portfolios.

2.3. Herding phenomena in commodity markets

Studies investigating herding phenomena have made their appearance earlier and this issue has attracted more attention lately. Pindyck and Rotemberg (1990), Cakan et al. (2019), and Júnior et al. (2019) constitute academic papers that look into this nexus. One of the initial papers has been Pindyck and Rotemberg (1990) that identify co-movements among the prices of raw commodities and argue that these commodities are seemingly unrelated. It is supported that this phenomenon could be attributed to the existence of herding behaviour during bull or bear markets.

In a somewhat different vein, Cakan et al. (2019) adopt firm-level data about Russia, Brazil and Turkey and reveal that there are frequent alterations between herding and non-herding conditions in these markets. Herding is more obvious in the case of Russia. Additionally, it is found that higher levels of herding result into higher levels of oil speculation in Russia and Brazil. As regards Júnior et al. (2019), they investigate beta herding in commodity markets by adopting the Hwang and Salmon (2004) model and the beta adaptation by Hwang et al. (2018) concerning a state-space model. Evidence is given of sentimental herding as regards food commodities. Furthermore, adverse herding is more intense in this type of commodities.

In an overall perspective, these studies reveal that hedging is influential on commodity markets both in bull and bear markets. Moreover, sentimental herding is observed concerning the food commodities markets. It is very important for investor decision-making that higher levels of herding in commodity markets lead to incentives for higher speculation. Therefore, herding phenomena result into higher risk appetite and attracts larger amounts of liquidity towards commodity markets. This increases profit opportunities for risky investors and could generate extreme conditions (bull or bear markets) in commodity markets, such as the oil market which is considered as a traditional asset.

2.4. Herding phenomena in derivatives markets

Derivatives markets have also been a topic of investigation regarding its nexus with herding phenomena. Academic work such as McAleer and Radalj (2013), Demirer et al. (2015), and Boyd et al. (2016) look into this interesting strand of academic work. To be more precise, McAleer and Radalj (2013) investigate futures positions in nine markets of the

Commodity Futures Trading Commission (CFTC). They reveal that herding among small traders exists concerning the Canadian dollar, the British pound, gold, the S&P500 and the Nikkei225 futures. Volatility among small traders is found to present spillovers only with Nikkei225 futures.

By their own approach, Demirer et al. (2015) employ a regime-switching model and provide evidence of herding phenomena in the markets of grains during periods of large fluctuations. Moreover, it is shown that large alterations in market values concerning the energy and metal sectors influence herding behaviour in the market for grains. It is also argued that the stock market does not exert effects on herding behaviour in the commodity futures market. Moreover, Boyd et al. (2016) examine whether herding exists among large speculative traders in thirty-two futures markets. Outcomes indicate the existence of herding in a modest level among hedge funds and floor brokers/traders. Overall, it is found that herding in hedge funds is not substantially different from herding in stock market and that it does not lead to destabilization of market prices.

A number of important findings emerge from studies that examine herding effects on derivatives markets. Evidence reveals that higher volatility is favourable for the appearance of herding phenomena. Nevertheless, there is also evidence that herding does not lead to destabilization of prices. It should be noted that herding in one market can cause large spillovers to other markets though not in a large extent. Overall, herding in derivatives markets is found to be modest and intensified in periods of high uncertainty. Small traders are more affected by herding in these markets. This provides interested investors with a compass about how derivatives prices are formed and informs that the derivatives market may be less susceptible to investor sentiment than is usually thought to be.

2.5. Herding phenomena in real estate markets

The increasing popularity of real estate as a field for investigation has led to a nmber of papers that examine the linkage between herding behaviour and real estate markets. Ro and Gallimore (2014), Babalos et al. (2015), and Akinsomi et al. (2018) constitute relevant studies. Ro and Gallimore (2014) argue that stock herding in the 159 real estate mutual funds (REMFs) examined is lower in Real Estate Investment Trust (REIT) stocks than other stocks. Empirical outcomes indicate that managers exhibit a tendency to sell winners. Overall, it is supported that herding does not constitute a superior strategy for investments by REMFs.

By adopting a different methodology, Babalos et al. (2015) use a Markov regime-switching model that captures herding under alternative market regimes and provide evidence that herding behaviour exists under the crash regime. This concerns almost all the US-listed REITs. On the contrary, the static model displays no evidence of herding. Furthermore, it is revealed that negative herding phenomena during extreme volatility regimes but turn into positive under crash regime for approximately every REIT sector. By their own perspective, Akinsomi et al. (2018) adopt the Chang et al. (2000) methodology and provide evidence about the existence of herding behaviour, directional asymmetry and a linear connection between volatility and herding concerning Turkish REITs. Furthermore, they reveal that herding persists and increases during stressed periods in markets. Higher fluctuations bring to the surface stronger herding phenomena.

It is clearly revealed that bear markets and high levels of fluctuations in markets strengthen herding phenomena. Moreover, it can be seen that herding is not a strictly preferable investment strategy in comparison to alternative strategies. These findings abide by the conclusions concerning the majority of financial markets as herding is found to emerge in a larger extent during bear markets. Thereby, real estate investors tend to follow decisions of other real estate investors in order to invest when market conditions are stressed. This explains in a considerable level how real estate bubbles can be created as investor sentiment can be so influential that could easily turn the pessimistic environment into an optimistic one and create bubbles that will later be ready to burst.

2.6. Herding phenomena in large and advanced versus weak or developing markets

There are some significant academic studies that investigate herding phenomena in large and advanced countries. To be more precise, Uchida and Nakagawa (2007), Chiang and Zheng (2010), Klein (2013), and Choi and Skiba (2015) are among them. More specifically, Uchida and Nakagawa (2007) employ the technique of Lakonishok et al. (1992) and provide evidence of herding phenomena in the Japanese domestic loan market. Furthermore, it is supported that irrational herding behaviour has taken place during the bubble period and this has cost 5 trillion yen of loan increase by city banks. It is also argued that herding exists among regional banks and among banks that are placed near with each other. Moreover, Chiang and Zheng (2010) provide evidence that herding takes place in advanced stock markets (except the US) as well as in Asian markets. Nevertheless, no herding is revealed in Latin American markets. Furthermore, they support that herding exists during both bull and bear markets. It is also argued that herding is realized in the crisis country of origin and contagion impacts appear that also influence neighbouring countries.

In his study, Klein (2013) adopts a Markov-switching Seemingly Unrelated Regression (SUR) model and reveals that in the US and the Euro area when high volatility is present, more persistent deviations from rational asset-pricing take place. Additionally, there are more intense spillovers between the markets. Overall, evidence reveals that after the global financial crisis and the dot.com bubble bursting, stock market values have been more sensitive to investor behaviour. When it comes to Choi and Skiba (2015), they support that institutional herding stabilizes prices in international markets. Moreover, by employing five alternative measures concerning information asymmetry, they provide evidence that institutional investors exhibit higher herding levels in markets with low information asymmetry, thereby high information transparency. It is further argued that institutional investors' herding behaviour is determined by correlated signals from fundamental information.

In an overall perspective, it can be argued that intense herding takes place in large and advanced markets during both bull and bear markets. Spillover effects are revealed from advanced countries towards neighbouring ones. Bubble burst leads to herding phenomena. Generally, herding phenomena are closely tied with advanced economies under extremely favourable or stressed conditions.

It should also be noted that a range of papers examining herding behaviour in smaller or emerging markets take place. Such studies are: Agudo et al. (2008), Tan et al. (2008), Lao and Singh (2011), Yao et al. (2014), Filip et al. (2015), Javaira and Hassan (2015), and Guney et al. (2017). In their study, Agudo et al. (2008) investigate whether herding phenomena exist in the management style of Spanish equity funds by employing the methodology of Lakonishok et al. (1992) and Sharpe's style analysis. They argue that significant herding behaviour takes place in value stocks, growth stocks and cash.

Tan et al. (2008) argue that herding is evident within both the Shanghai and Shenzhen A-share markets that are dominated by domestic individual investors as well as within both B-share markets, where mainly foreign institutional investors participate. This is found to be valid both in bull and bear markets. Additionally, more intense herding is revealed for A-share investors in the Shanghai market during bull markets, high trading volume and large fluctuations in prices. In a somewhat similar vein, Yao et al. (2014) examine the same sectors as Tan et al. (2008) and argue that levels of herding are not equal among investors. The B-share markets are found to present powerful herding phenomena. It should be noted that herding is revealed to be stronger during bear markets and evidence indicates that it fades out over time.

Lao and Singh (2011) provide evidence that herding phenomena exist in Chinese as well as in Indian stock markets but in a lesser extent and the

intensity of these phenomena varies according to market conditions. Herding levels are higher in China when bear markets and high trading volumes exist while is more intense in bull markets in India. Large fluctuations in markets are found to favour herding behaviour.

Moreover, Filip et al. (2015) employ firm-level data and use the cross-sectional absolute deviation (CSAD) measure by Chang et al. (2000) in order to examine herding in Central and Eastern European (CEE) countries. It is revealed that all stock markets in CEE countries with the exception of Poland exhibit herding behaviour. This phenomenon is found to happen during both bull and bear markets. In their study, Javaira and Hassan (2015) argue that no herding took place at the Karachi Stock Exchange in Pakistan. Asymmetry in market returns, high and low volume conditions and asymmetries in market volatility are not revealed to have led to herding phenomena. Furthermore, macroeconomic factors are not found to have been influential. Despite that, evidence of herding exists during the liquidity crisis of March 2005 because of information asymmetries among investors and the existence of speculation. By focusing on African studies, Guney et al. (2017) support that herding exists in eight African frontier markets and that smaller stocks strengthen the level of herding. It appears that herding is largely asymmetric under the conditions of low market volatility. It is also found that markets that are only slightly integrated into the international financial system present herding behaviour that is not significantly influenced by non-domestic determinants.

All in all, herding is found to be more intense during bull but also bear markets as concerns European as well as African countries and China. India presents less strong herding phenomena that are evident during flourishing times. Countries not tightly tied to the international system are not receivers of herding influences from other countries. Pakistan is found not to exhibit significant herding behaviour. Moreover, asymmetries are detected in the African countries examined.

Overall, when conducting a comparison between herding in advanced and herding in developing markets it can be seen that both advanced and developing economies present more intense herding behaviour during extreme rather than normal times. It is noteworthy that developing countries such as China that are upcoming powerful markets present similarities in herding phenomena with developed markets such as the US, Japan and the Euro area. Internationalization of markets is found to be important for herding received by spillovers from other countries. This can provide some useful guidance to international investors as advanced markets are more predictable as concerns their herding behaviour in relation to developing markets.

3. Studies revealing herding behaviour in digital currency markets

3.1. Studies presenting strong herding behaviour in cryptocurrency markets

It is very interesting that empirical academic papers with meaningful outcomes about herding behaviour in the markets of digital currencies have been brought about. A significant portion of the embryonic academic research on herding behaviour in cryptocurrency markets provides evidence that strong herding phenomena exist. To be more precise, Ballis and Drakos (2020), da Gama Silva et al. (2019), Kaiser and Stöckl (2020), and Kallinterakis and Wang (2019) support this perspective.

More specifically, Ballis and Drakos (2020) employ daily data concerning Bitcoin, Ethereum, Litecoin, Monero and Dash covering the period from August 2015 to December 2018. They adopt the cross-sectional standard deviation (CSSD) and the cross-sectional absolute deviation (CSAD) methodologies in order to trace herding phenomena in markets of major cryptocurrencies. Furthermore, Newey-West and GARCH estimations are conducted. They test the hypothesis that different behaviour exists in up or down movements. Empirical outcomes reveal that market dispersion movements are less than proportionate to fluctuations of market returns. Moreover, it is found that market dispersion during up-events is faster in comparison to the down-events. Thereby, asymmetric herding behaviour exists. In a partly similar mentality, da Gama Silva et al. (2019) analyze herding behaviour of 50 very liquid and capitalized digital currencies spanning the period from March 2015 to November 2018. The CSAD and the CSSD methodologies are employed as well as Hwang and Salmon's (2004) model to analyze herding behaviour. Furthermore, adaptations of Forbes and Rigobon's (2002) test and extensions based on Fry et al. (2010) and Fry-McKibbin and Hsiao (2018) are adopted for measuring contagion. Findings reveal herding behaviour and extreme periods of adverse herding phenomena are detected in periods of high risk aversion. Additionally, it is shown that Bitcoin is contagiously influential to the other cryptocurrencies.

Moreover, Kaiser and Stöckl (2020) by proposing Bitcoin as a "transfer currency" provide evidence that herding measures around such a currency present to researchers a more precise picture of herding behaviour in the cryptocurrency market. The CSAD methodology is employed. They support that the market of digital currencies is characterized by a large level of irrationality regarding investors' decisions and significant herding behaviour that leads to high levels of volatility. As regards Kallinterakis and Wang (2019), they look into herding phenomena in the cryptocurrency markets and their causes during the December 2013–July 2018 period. The CSAD measure and dummy variables about high volume and high volatility days are adopted. Results indicate that herding is considerable and is found to be more powerful during upwards tendencies in digital currency markets. Furthermore, smaller-capitalization cryptocurrencies reinforce the level of herding. Moreover, the cryptocurrency market is found to entail great destabilization risks.

3.2. Studies revealing weak or mixed results about herding behaviour in cryptocurrency markets

Moreover, there is a smaller number of academic papers that provide evidence towards the existence of weak herding behaviour or mixed results as concerns the crytpocurrency markets. Such evidence can be found at the studies of: Bouri et al. (2019), Stavroyiannis and Babalos (2019), and Vidal-Tomas et al. (2019).

Bouri et al. (2019) adopt a GSAD methodology in order to study herding behaviour in the markets of digital currencies. Moreover, they identify structural breaks and non-linearities and adopt rolling-windows for estimations. Furthermore, the Probit model is employed and the Economic Policy Uncertainty (EPU) index is adopted in estimations. Daily data about Bitcoin, Ethereum, Ripple, Litecoin, Stellar, Dash, Nem, Monero, Bytecoin, Verge, Siacoin, BitShares, Decred and Dogecoin are used. The period under scrutiny starts from 28 April 2013 and covers until 2 May 2018. Outcomes provide evidence that significant herding phenomena exist during the sub periods a) 24 April 2016 to 28 November 2016, b) 5 January 2017 to 1 April 2017, c) 21 May 2017 until 29 May 2017 and d) 20 July 2017 until 13 September 2019. The authors argue that herding exists in cryptocurrency markets but its intensity is not stable over time. The static model finds no evidence of herding while probit results support that higher uncertainty intensifies herding phenomena. Moreover, Stavroyiannis and Babalos (2019) employ Ordinary Least Squares (OLS), the time-varying parameter (TVP) and quantile regression methodologies in order to trace herding behaviour in virtual currencies from 9 August 2015 until 18 February 2018. Moreover, the CSSD and CSAD specifications are employed. Herding behaviour is examined through a static as well as a dynamic analysis lens. Results present that herding is more intense during bull markets in comparison to bear markets. This abides by the findings of Vidal-Tomas et al. (2019). The time-varying model used reveals the lack of herding phenomena in the cryptocurrency markets.

When it comes to Vidal-Tomas et al. (2019), they investigate herding behaviour related to an equally-weighted market portfolio. The daily data employed cover 65 digital currencies during the period from 1 January 2015 to 31 December 2017. The cross-sectional standard deviation of returns (CSSD) and the cross-sectional absolute deviation of returns (CSAD) models are employed for examination. Robustness estimations take place by adopting cap-weighted apart from equally-weighted market portfolios. It is argued that extreme price movements in the tails of distributions do not provide evidence for herding behaviour. Moreover, evidence shows that herding is more perceptible during down markets rather than during bull periods. Bitcoin, Ripple, Litecoin, Dash and Stellar are estimated to be the dominant and most influential of the digital currencies examined. When Bitcoin is absent in portfolios then the other major cryptocurrencies take its role. It should be noted that Bitcoin cannot create by itself the herding phenomenon. Furthermore, emphasis should be paid in that no evidence of herding is detected based on the cap-weighted market portfolio analysis.

In another innovative perspective, Yarovaya et al. (2020) employ hourly data and CSAD, quantile and time-varying regression methodologies in order to examine herding behaviour in the most traded cryptocurrency markets during the January 2019–March 2020 period. Empirical outcomes indicate that while the COVID-19 increased fluctuations in markets of digital currencies, herding phenomena became weaker especially in the USD and Euro cryptocurrency markets. Moreover, Philippas et al. (2020) propose a novel approach where extracted signals are endogenized in investors' decision-making in order to study herding intensity in cryptocurrency markets. Econometric evidence reveals the existence of substantial asymmetries as regards such intensity. Considerable diversity in the value assigned to relevant signals is traced. It is supported that Bitcoin-related tweets and Google searches amplify herding phenomena whereas patterns in policy uncertainty and the linkage of equity and foreign exchange markets lead to lower herding.

It can be seen that the majority of studies on herding phenomena in digital currency markets have employed the CSAD and the CSSD methodologies though findings are far from identical. It is evident that studies having employed both the CSAD and CSSD measures provide mixed results about whether herding is stronger during bull or bear markets. It should be noted though that empirical papers that adopt solely the CSAD methodology reveal that herding is more powerful during bear markets. In an overall sense, there is that Bitcoin remains among the most influential cryptocurrencies though the level of this dominance and the periods during which this exerts herding effects is not unanimous across studies. Most relevant papers indicate that herding is stronger during bull markets (Kallinterakis and Wang, 2019; Stavroyiannis and Babalos, 2019) but there are also fewer studies that support higher herding intensity during bear markets (Vidal-Tomas et al., 2019). The periods of high herding influences vary substantially as concerns their duration. Thereby, it is seen that they could last some days, a couple of months or even half a year approximately. It is quite interesting that when Bitcoin is not capable of influencing prices of other cryptocurrencies even some small-capitalization digital currencies prove influential in a certain degree for short time periods.

4. Data and methodology

Apart from a survey on academic work related to herding phenomena, this study undertakes the task of estimating herding phenomena in cryptocurrency markets during bull and bear markets. For the purposes of estimations, data are employed spanning two separate sub periods. The first sub period covers from 1 January 2017 until 18 December 2017 when the Bitcoin bubble when the bubble of this market is considered to have burst (Wheatley et al., 2018). This represents the bull period in markets of digital currencies. Moreover, estimations take place as concerns the period from 19 December 2017 up to 15 December 2018 that the abrupt fall in market values of digital currencies ended. Thereby, this stands for the bear market of cryptocurrencies. In order to examine herding phenomena in the markets of digital currencies data about 240 high-, medium- or low-capitalization cryptocurrencies have been extracted by the *coinmarketcap.com* database.[1] Furthermore, the S&P500 index has been employed to represent the benchmark market index. This data has been downloaded from the *Yahoo Finance* website.

The methodology adopted so as to trace whether herding behaviour exists or not during extreme conditions in the markets of digital currencies, is the cross-sectional absolute deviation (CSAD) by Chang et al. (2000) and based on Gleason et al. (2004) and Chiang and Zheng (2010), which is expressed as follows:

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

Chang et al. (2000) also use the following regression model:

$$CSAD_t = \alpha + \gamma_1\left|R_{m,t}\right| + \gamma_2 R_{m,t}^2 + \varepsilon_t$$

Where $\left|R_{m,t}\right|$ shows the absolute equally-weighted market return and $\left|R_{m,t}^2\right|$ displays the squared market return. Chang et al. (2000) support that if the γ_2 coefficient is negative and statistically significant then herding behaviour exists. On the other hand, if there is no herding phenomenon detected then higher market returns lead to higher dispersion.

5. Empirical findings and economic implications

A number of significant outcomes emerge when estimating herding behaviour during bull and bear cryptocurrency markets.

Figure 1 presents how the CSAD measure evolved over time during the bull and bear market. It can be seen that larger fluctuations in herding are evident during bull markets but more frequent alterations are presented during bear markets.

Summary statistics in Table 1 present that the CSAD measure is found to be larger during bull markets. Moreover, based on the levels of skewness, kurtosis and the Jarque-Bera statistic, it is revealed that the CSAD is more asymmetric during bear markets.

Econometric outcomes reveal that herding behaviour exists in cryptocurrency markets during the bull period (see Table 2). This is shown as the coefficient of SP500̂2 exhibits a negative sign. Nevertheless, it can be seen that this coefficient is not statistically significant. Moreover, the overall statistical significance of estimations is found to be low. Based on the negative coefficient, it is supported that the markets of digital currencies have been inefficient during bull tendencies and the driving factor of the cryptocurrency market is the mean return of the major digital currencies. The findings about herding in cryptocurrency markets during the bull period are in accordance with the outcomes by Ballis and Drakos (2020). Thereby, investors exhibit the tendency to invest in digital currencies based on information about the returns of the largest cryptocurrencies.

It should be emphasized though that results about the bear market are not in accordance with findings about the bull market except for the overall low statistical significance of estimations. During downwards tendencies in cryptocurrency markets, no herding phenomena are traced as the coefficient of SP500̂2 is found to be positive and statistically non-significant. This leads to the conclusion that during the abrupt fall in market values in 2018, the markets of digital currencies have moved towards higher levels of efficiency. Consequently, fewer opportunities for profitable trading and speculation have made their appearance during the bear market. It can be argued that investors do not follow the market consensus when prices are falling. This is in contrast to findings by Vidal-Tomás et al. (2019).

[1] Table 1A in the Appendix provides a list with all the cryptocurrencies examined in this study.

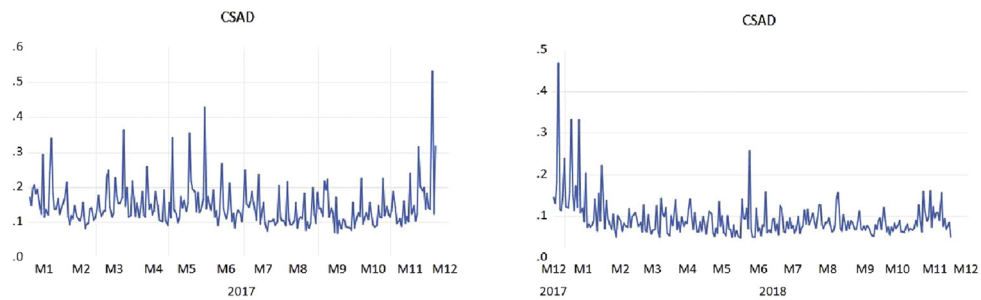

Figure 1. CSAD during bull and the bear market.

Table 1. Descriptive statistics of CSAD during bull or bear markets.

	Bull_Market	Bear_Market
Mean	0.1474	0.0945
Median	0.1331	0.0823
Max	0.5328	0.4689
Min	0.0697	0.0485
Std.Dev.	0.0606	0.0462
Skewness	2.4446	3.8185
Kurtosis	12.1554	25.1707
JB	1086.223 (0.000)***	5681.938 (0.000)***
Obs	242	248

Table 2. Estimation results of regressions in bull and bear markets.

	Bull_Market	Bear_Market
α	0.1477 (0.000)***	0.0923 (0.000)***
γ_1	0.1551 (0.8673)	0.1513 (0.6477)
γ_2	-23.8655 (0.8140)	22.2623 (0.1577)

6. Discussion and conclusions

This study is an integrated survey on herding phenomena in financial assets with special emphasis on the markets of digital currencies. An important number of important academic papers have been employed in this paper in order to provide in the clearest way a bird's-eye view on different aspects of herding behaviour in financial markets.

Findings about herding phenomena in markets of traditional assets reveal that investors present an inclination towards irrational behaviour and mimicking others' decisions which is more emphasized during turbulent market periods. Nevertheless, outcomes are split concerning whether bull markets are more able to provide higher herding incentives than bear markets. It should be noted though that during normal economic conditions no evidence of herding is brought to the surface. Distortions in the rational thinking of economic units are detected in a range of financial assets. Remarkably though, it is stock markets that are found to be mainly influenced by distortions in investors' beliefs.

When it comes to the markets of digital currencies, it can also be seen that the CSAD and CSSD methodologies are popular among academic investors but also more innovative methods of estimations have emerged. Arguably, evidence indicates that Bitcoin remains the dominant and among the most influential cryptocurrencies though other highly-capitalized digital currencies such as Ethereum or Litecoin can also exert herding behaviour during certain periods. The CSAD methodology reveals that herding is more intense during bear markets while studies employing both the CSAD and CSSD measures provide mixed results about herding phenomena in bull and bear markets. Remarkably, evidence reveals that even lower-capitalization currencies could influence herding phenomena in markets of digital currencies. Furthermore, the majority of studies indicate that bull markets can trigger more intense herding behaviour than bear ones but the latter remain generators of distortions and mimicking. These findings contribute to a much better understanding of the hotly-debated issue of investments in markets of digital currencies and casts light on the factors that spur irrationality in human behaviour among investors.

This survey examines and analyzes the nexus of herding phenomena with a spectrum of financial assets, such as stocks, bonds and funds, commodities, derivatives, the real estate and cryptocurrencies. Moreover, studies based on micro-data have been investigated. Furthermore, a comparative analysis takes place between herding phenomena in large and advanced in comparison with weak and developing markets. Overall, it is found that markets present higher levels of herding behaviour during bear markets.

There is a threefold contribution of this paper. Firstly, understanding of rational and irrational behaviour is improved and an overall view on herding phenomena in financial markets is provided. Secondly, we conduct a comparative analysis of herding behaviour across markets. Thirdly, an empirical estimation of herding is takes place by using data on a respectable number of digital currencies and comparison is made between bull and bear periods.

In a general viewpoint, evidence reveals that herding behaviour is detected in stock markets during both bull and bear periods. Moreover, herding is found to be influential on lower quality bonds which are prone to be employed for the purposes of speculation. These findings are in tandem with papers about impacts on commodity markets. Higher levels of herding in commodity markets are revealed to lead to incentives for higher speculation. Therefore, herding phenomena develop higher risk appetite and attracts larger amounts of liquidity towards commodity

markets. Furthermore, as concerns derivatives markets, it is shown that herding is modest and gets stronger in periods of high uncertainty. Small traders are more influenced by herding in derivatives markets. Moreover, when it comes to real estate markets, bear periods and high levels of volatility in markets are found to strengthen herding behaviour.

In a different perspective, this overview argues that in studies employing micro-data herding is stronger concerning small stocks in extreme conditions, especially bear markets while large stocks are found to exhibit herding behaviour mostly during normal times. It is also of great interest to conclude that advanced economies exhibit a more or less uniform herding behaviour wheras emerging economies are mostly affected during bear markets especially when non-European countries are under scrutiny. It should be noted though that developing countries such as China that are highly promising markets present resemblances with developed markets such as the US, Japan and the Euro area as regards herding phenomena.

When it comes to the central issue of this study, that is the nexus between herding and cryptocurrencies, it can be seen that studies having adopted both the CSAD and CSSD measures present mixed results about whether herding is more influential during bull or bear markets. It should be emphasized that academic studies that use only the CSAD methodology provide evidence that herding is stronger during bear markets. In an overall sense, there is that Bitcoin remains among the most influential cryptocurrencies though the level of this dominance and the periods during which this exerts herding effects is not unanimous across studies. In a general perspective, bear conditions are found to be slightly more favourable for the presence of herding phenomena in the markets of digital currencies.

Moreover, this study has conducted empirical estimations about 240 high-, medium-, or low-capitalization cryptocurrencies during bull and bear markets. Findings indicate herding behaviour exists in cryptocurrency markets during the bull period while this does not hold as concerns the bear market. These results are not statistically significant regarding the bull market but are more reliable concerning the bear market, These outcomes do not abide by the majority of literature that supports impacts of herding being more influential on financial markets during stressed eras when it comes to cryptocurrencies or other financial assets as explained above.

The main aim of this study is to provide an overall perspective of herding phenomena that are primarily based on distortions in economic rationality of participants in the markets of conventional and especially modern forms of liquidity and investments. This integrated survey could provide a roadmap for investment decisions and contribute even in the slightest degree to better understanding of digital currencies that would give feedback for further research in this very interesting domain of economics and finance. Avenues for future investigation of digital forms of money could include estimations with alternative methodologies. Moreover, a larger spectrum of digital currencies could be covered in estimations. It would be very interesting to conduct empirical research focusing on the nexus between herding intensity in cryptocurrency markets with herding levels in markets of alternative (substitute or complementary) forms of investments. Research could also take place under alternative weighting schemes of digital currencies in portfolios. This examination could take place in bull, normal or bear markets and emphasis on higher or lower quantiles of distributions could be put. Moreover, convergence among cryptocurrency clubs and its impacts on efficiency of digital currency markets could be examined in future empirical papers.

Declarations

Author contribution statement

All authors listed have significantly contributed to the investigation, development and writing of this article.

Funding statement

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Competing interest statement

The authors declare no conflict of interest.

Additional information

No additional information is available for this paper.

Appendix

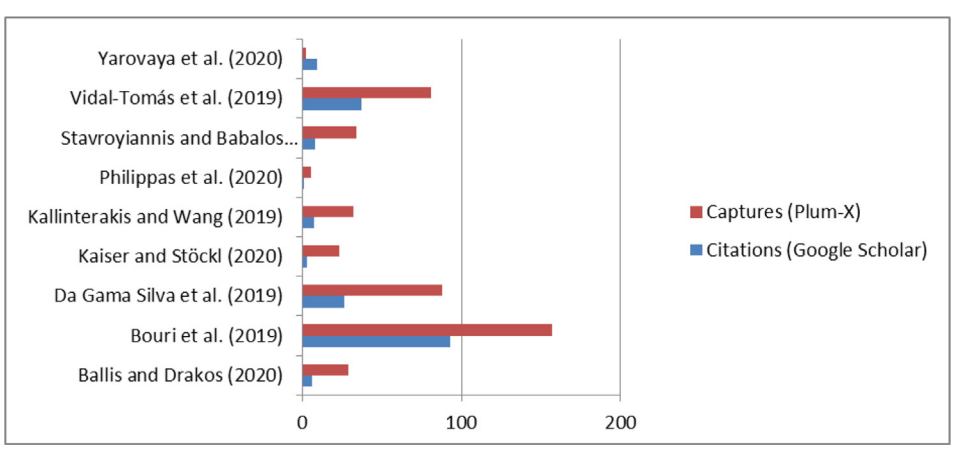

Figure A1. Citations by Google Scholar and Plum-X captures per study (as in 17 August 2020).

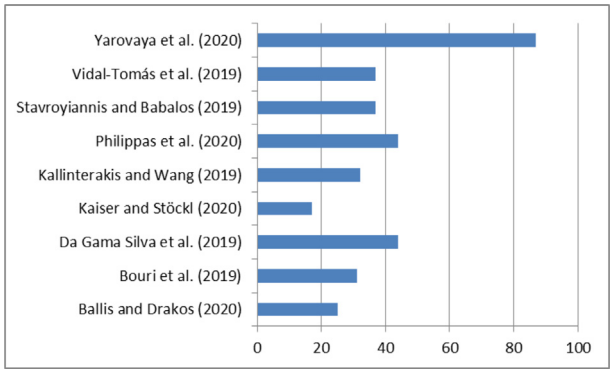

Figure A2. Total academic references on which each study examined has been based.

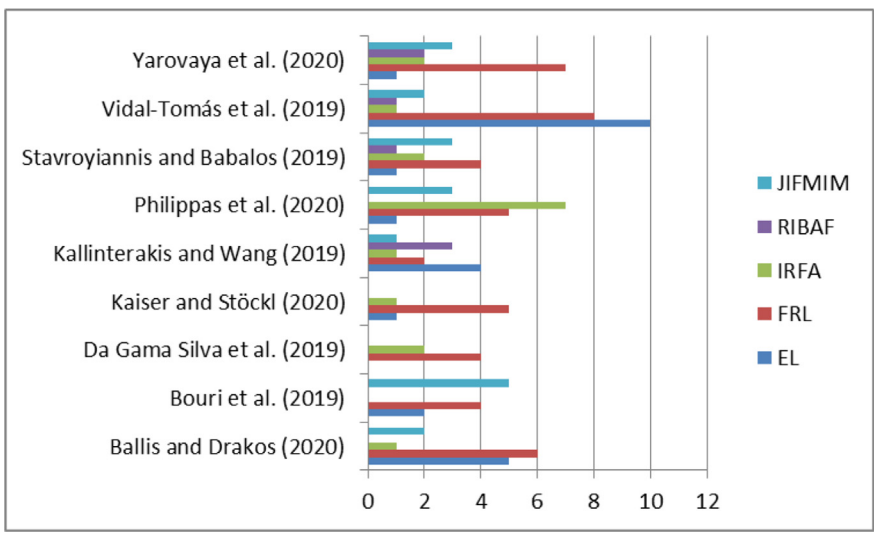

Figure A3. References that have been taken by the most popular journals about digital currencies. *Notes*: EL, FRL, JIFMIM, IRFA and RIBAF stand for Economics Letters, Finance Research Letters, Journal of Financial Markets, Institutions and Money, International Review of Financial Analysis and Research in International Business and Finance.

Table 1A. List of the cryptocurrencies involved in estimations about herding behaviour.

BTC	DCR	SLR	XBC	XST	EL	ZEIT	FJC
ETH	NAV	IOC	LMC	VRM	PAK	CJ	EMD
LTC	NMC	VIA	EGC	OBITS	THC	ENT	CHESS
XMR	EMC	BAY	YOC	INCNT	TIT	ADC	1337
DASH	XCP	RADS	EFL	PEPECASH	QRK	HUSH	SONG
ETC	LEO	RBY	CRB	KRB	BLC	IXC	HODL
XRP	LBC	EMC2	SHIFT	SFT	BITBTC	BITGOLD	ION
ZEC	1ST	FTC	XMG	DGC	BERN	PLU	DP
FCT	DGB	GRC	OK	GOLOS	MEME	KURT	611
MAID	EXP	VRC	ADZ	BLOCK	BITS	2GIVE	EVIL
DOGE	XZC	XDN	POST	DEM	ORB	NEVA	KOBO
REP	CLAM	XMY	MUE	BTA	XCN	LANA	ACP
XEM	NEO	OMNI	IOP	ARC	SJCX	TAJ	BSC
XLM	SBD	BELA	DMD	XVG	EXCL	BLU	PURA
BTS	BURST	PINK	VSL	GB	SPHR	SYNX	ANC
LSK	BITCNY	CURE	WDC	MOIN	PXI	RBT	HYP
GAME	DGD	BCN	BSD	ATOM	MOJO	SRC	BUMBA
NXT	NLG	FLO	SEQ	DOPE	HEAT	SMC	FUZZ
STEEM	VTC	SNGLS	CANN	SLS	BTB	ARG	ECC
SC	NXS	CPC	CRW	PTC	ESP	ACOIN	XCO
STRAT	XPM	PIVX	TRC	GRS	BITSILVER	ARCO	XPY
PPC	XAUR	AUR	TRUMP	XWC	BOLI	ZNY	MOTO
WAVES	RVR	MONA	RDD	SPR	MAX	ELE	CMT
EDRC	BCY	GCR	RISE	TAG	VLT	PKB	MXT
ARDR	FLDC	AEON	TX	NSR	SWING	CF	XPD
POT	NVC	BITUSD	PUT	TIPS	C2	TROLL	PND
SYS	XHI	START	ABY	BSTY	RBIES	NTRN	HVCO
GNT	ZCL	UNO	ZET	FAIR	MINT	XRA	UNIT
AMP	GBYTE	USNBT	PASC	WBB	NLC2	DUO	LDOGE
BLK	SIB	CLOAK	CREVA	BIT	BTCS	FRN	AIB

Table 2A. Main characteristics and findings of studies focusing on herding behaviour in digital currency markets

Authors	Journal	Variables	Data source	Period examined	Methodology	Existence of Herding
Ballis and Drakos (2020)	FRL	Bitcoin Dash Ethereum Litecoin Monero Ripple	Cryptocompare.com Coinmarketcap.com	August 2015–December 2018	Cross-sectional absolute deviations (CSAD) by Chang et al. (2000) Cross-sectional standard deviations (CSSD) by Christie and Huang (1995) GARCH by Bollerslev et al. (2016)	There is herding and is more pronounced in bull markets
Bouri et al. (2019)	FRL	Bitcoin Ethereum Ripple Litecoin Stellar Dash Nem Monero Bytecoin Verge Siacoin BitShares Decred Dogecoin	Coinmarketcap.com	28 April 2013–2 May 2018	Cross-sectional absolute deviations (CSAD) by Chang et al. (2000)	Significant herding during 4 periods: (24 April 2016–28 November 2016, 5 January 2017–1 April 2017, 21 May 2017–29 May 2017, 20 July 2017–13 September 2017), especially from April 2016 to September 2017
da Gama Silva et al. (2019)	JBEF	CRIX Bitcoin Ethereum Ripple Stellar Lumens	Crix.hu-berlin.de Coinmarketcap.com	March 2015–November 2018	Cross-sectional absolute deviations (CSAD) by Chang et al. (2000) Cross-sectional standard deviations (CSSD) by	Positive herd effect (beginning of 2015) Adverse herding (May 2015–November(2015) Positive herd effect (mid-

(*continued on next page*)

Table 2A (*continued*)

Authors	Journal	Variables	Data source	Period examined	Methodology	Existence of Herding
		Litecoin Monero Tether Dollar Dash Dogecoin BitShares Bytecoin DigiByte Verge MaidSafeCoin Monacoin Reddcoin Nxt Syscoin Peercoin Nexus Groestlcoin VertCoin Einsteinium Ubiq Blocknet NavCoin BitCNY Novacoin DigitalNote ViaCoin BitBay Burst WhiteCoin CloakCoin Boolberry Unobtanium Gulden BitUSD GameCredits CassinoCoin Counterparty Namecoin Feathercoin PrimeCoin Crown FlorinCoin BlackCoin ECC Diamond PotCoin			Christie and Huang (1995) FR test for parametric contagion by Forbes and Rigobon (2002) Coasymmetry test by Fry et al. (2010) Cokyrtosis test by Fry-McKibbin and Hsiao (2018) Covolatility test by Fry-McKibbin and Hsiao (2018)	December 2015–March 2016) Predominant herd effect (end June 2016–September 2016) Reversal of herd effect (end September 2016–February 2017) Herd effect (end February 2017–April 2017) Reversal in the herd impac (May 2017–July 2017) Prominent herd effect (August 2017–September 2017) Reversal of herd effect (November 2017–September 2017) Pessimism influences herd effect during 2018
Kaiser and Stöckl (2020)	FRL	Ranging from 395 to 2026 digital currencies	Coinmarketcap.com	1 January 2015–25 March 2019	Cross-sectional absolute deviations (CSAD) by Chang et al. (2000)	Bitcoin is a "transfer currency" and leads to herding
Kallinterakis and Wang (2019)	RIBAF	The top 296 cryptocurrencies	Coinmarketcap.com	27 December 2013–10 July 2018	Cross-sectional absolute deviations (CSAD) by Chang et al. (2000)	Significant herding (irrespective of Bitcoin and its trends), strongly asymmetric (is more powerful during bull markets, low-volatility and high-volume periods) and smaller digital currencies reinforce its size
Philippas et al. (2020)	JIFMIM	Top 100 cryptocurrencies in terms of volume	Coinmarketcap.com Various sources	January 2016–May 2018	Cross-sectional absolute deviations (CSAD) by Chang et al. (2000) Examination of signal-herding by extracting signals from market indices, media attention indices, risk and uncertainty indicators.	Bitcoin-related tweets and Google searches intensify herding phenomena whereas patterns in policy uncertainty and the linkage of equity and foreign exchange markets result in weaker herding
Stavroyiannis and Babalos (2019)	JBEF	Bitcoin Ethereum Ripple Litecoin Dash Nem Monero Stellar	Coinmarketcap.com	9 August 2015–18 February 2018	Cross-sectional absolute deviations (CSAD) by Chang et al. (2000) Cross-sectional standard deviations (CSSD) by Christie and Huang (1995) Time-varying parameter regression model by	No herding

(*continued on next page*)

Table 2A (*continued*)

Authors	Journal	Variables	Data source	Period examined	Methodology	Existence of Herding
					Nakajima (2011) Ordinary Least Squares (OLS) with Heteroskedasticity and Autocorrelation corrected standard errors (HASCE) by Newey and West (1987)	
Vidal-Tomás et al. (2019)	FRL	65 digital currencies available in the BraveNewCoin database	BraveNewCoin database Coinarketcap.com	1 January 2015–31 December 2017	Cross-sectional absolute deviations (CSAD) by Chang et al. (2000) Cross-sectional standard deviations (CSSD) by Christie and Huang (1995)	Herding during down markets. The smallest cryptocurrencies are herding with the largest ones. Not only Bitcoin is responsible for herding
Yarovaya et al. (2020)	SSRN	Bitcoin, Litecoin, Ethereum in the USD and the Euro cryptocurrency market Bitcoin, Bitcoin Cash, Litecoin, Ethereum, MonaCoin, NEM and Zaif in the JPY market Bitcoin, Bitcoin Gold, Ethereum, Litecoin, Monero and Ripple in the KRW market	www.cryptodatadownload.com/	1 January 2019–13 March 2020	Cross-sectional absolute deviations (CSAD) by Chang et al. (2000) Newey and West (1987) estimations Quantile regressions as in Sim and Zhou (2015) Time-varying regressions as in Bollerslev et al. (2016)	Unconditional herding in all except for the KRW cryptocurrency market COVID-19 increased volatility in markets of digital currencies, but herding phenomena became weaker especially in the USD and Euro cryptocurrency markets

Notes: FRL, JBEF, JIFMIM, RIBAF and SSRN stand for Finance Research Letters, Journal of Behavioral and Experimental Finance, Research in International Business and Finance and Social Science Research Network, respectively.

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