Behavioural finance and cryptocurrencies

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Abstract

The present study sets out to examine the empirical literature on the behavioural aspects of cryptocurrencies, showing the findings of related studies and discussing the various results. A systematic literature review of cryptocurrencies in behavioural finance seems to be timely and particularly important in terms of providing a guide for future research. Key topics include an extent review on the issue of herding behaviour among cryptocurrencies, momentum effects and overreaction, contagion effect, sentiment and uncertainty, along with studies related to investment decision making, optimism bias, disposition, lottery and size effects.

Keywords: Behavioural Finance; Bitcoin; Cryptocurrencies; Herding; Momentum; Sentiment

JEL classification: G4; G1

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1. Introduction

"It doesn't do anything. It just sits there. It's like a seashell or something, and that is not an investment to me"

Warren Buffett

Over the course of the past decade, following the creation of Bitcoin – the first cryptocurrency – there has been a proliferation of new cryptocurrencies (10,000+), attracting both investor's attention and capital. As of 13 November 2021, the total capitalization of the cryptocurrency markets stands well above 2.5 trillion dollars. Hence, it is ostensible that the cryptocurrency market has exhibited a significant increase both in its intensive, as well as its extensive margins (Ballis and Drakos, 2021). To a layman, the cryptocurrency market may be synonymous only to high returns and extreme volatility, however this has proved to be a holistic approach leading to erroneous conclusions regarding the dynamics pertinent to the cryptocurrency market.

The objective of this study is to offer a systematic review of the empirical literature on behavioural finance and cryptocurrencies, by discussing questions examined and main findings, and providing some avenues for future research. Our survey paper complements recent papers in the area by offering a systematic account on the influence of behavioural factors on cryptocurrencies (see Corbet *et al.*, 2019). Further, this study's purpose is not just to index the relevant literature, but rather to showcase and pinpoint several research areas that have emerged in the field of behavioural cryptocurrency research. For all these reasons, a systematic literature review of cryptocurrencies in behavioural finance seems to be timely and particularly important.

Even though a chronological review of the literature might demonstrate historical developments in the area of cryptocurrencies, studies on the behavioural aspects of cryptocurrencies include a wide range of issues. As a result, the research in this study is arranged both topically and chronologically in order to present a more comprehensive picture. Instead, we focus on four different aspects of behavioural finance: herding behaviour, momentum and overreaction effects, contagion effects, investor sentiment and uncertainty, and biases in investment decision making.

The remainder of the paper is structured as follows. Section 2 offers an extent review on the issue of herding behaviour among cryptocurrencies. We continue the literature review with section 3 which describes the presence of momentum effects and overreaction in the cryptocurrency market, and in section 4 we review and discuss studies related to the contagion effect. Afterwards, section 5 deals with the issue of sentiment (investor's, market's) and uncertainty, along with search volume predictability. In section 6, we discuss studies that explore investment decision making, optimism bias, disposition, lottery and size effect. Finally, Section 7 concludes and indicates niches for potential research.

2. Herding in cryptocurrencies

Herding behaviour, as a notion, has been examined by various academic disciplines, ranging from biology and psychology to economics and finance. In humans, herding is described as a coordinated social activity caused by local contacts between a group of individuals and characterised by the lack of a central control mechanism. Despite the absence of centralised coordination, the herd's structure is sustained as a result of emergent local interactions (Raafat *et al.*, 2009). Bertrand Russell (1950) stated that, "*Neither a man nor a crowd nor a nation can be trusted to act humanely or to think sanely under the influence of a great fear*". Many definitions of herding have been presented in the context of economics and finance. Herding, in a wide sense, is the same behavioural pattern used by economic agents collectively and simultaneously as a result of their copying behaviour.

Stocks and other commodities are always exchanged at their fair values, according to the Efficient Market Hypothesis (EMH) scenarios. However, it is not rare for capital markets to go afoul of the EMH's rationality assumptions in various cases. According to the findings of Bikchandani and Sharma (2001), herding behaviour describes a group of people acting impulsively and mimicking others' actions without regard for their own opinions. As previously stated, herding behaviour is a well-known concept that has been studied in a variety of domains, among which is the examination over its attributes in the cryptocurrency market.

Table 1 describes all the related studies discussed in this section. Furthermore, we split the literature into three sub-categories. In section 2.1 we discuss studies that suggest the presence of herding behaviour among cryptocurrencies (Table 1, Panel A), whereas in section 2.2 we include the ones that suggest otherwise or are inconclusive (Table 1, Panel B). Finally, in section 2.3 we include the strand of the literature concerning herding behaviour among cryptocurrencies during the COVID-19 pandemic (Table 1, Panel C).

Table 1

2.1 Strong and moderate herding effects

Bouri *et al.* (2019) investigate the presence of herding behaviour in the cryptocurrency market. The authors perform a rolling-window study, and the findings indicate that there is considerable herding behaviour that fluctuates over time. Additionally, by using a logistic regression, they find that herding tends to occur as uncertainty increases. Da Gama Silva *et al.* (2019) analysed herding behaviour and contagion phenomena in the cryptocurrency market. For the purposes of their research 50 of the most liquid and capitalized cryptocurrencies were selected, and by employing the cross-sectional absolute deviation (CSAD) and cross-sectional standard deviation (CSSD) tests, their results revealed herding behaviour, demonstrating extreme periods of adverse herd behaviour. Building up on that Vidal-Tomás *et al.* (2019) observed in their analysis of 65 digital currencies, that the smallest cryptocurrencies are herding with the largest ones, whereas the results of Kallinterakis and Wang (2019) suggest that, besides herding and asymmetry (stronger during up-markets), the cryptocurrency market entails strong destabilizing potential, the latter being of particular relevance to the authorities entrusted with its regulatory treatment. Similarly, the analysis of Ballis and Drakos (2020) provide evidence that the up-events market dispersion follows market movements at a faster pace compared to the down events.

Continuing with the relevant literature, the study of Kumar (2020) finds that herding is pronounced when the market is either passing through stress or has become highly volatile. Furthermore, the author states that anti-herding is found in a less volatile market or in a bullish market. Similarly, Kyriazis (2020) empirically investigates herding behaviour among 240 cryptocurrencies during bull and bear markets. The empirical estimations of the study reveal that herding behaviour is evident only in bull markets. In their research, Jalal *et al.* (2020), look into herding behaviour in cryptocurrencies in a variety of scenarios. The presence of herding is confirmed in cryptocurrencies in the upper quantiles during bullish and high volatility times due to investor overexcitement, which leads to large volume trading. However, their study suggests no evidence of an intra-dependency impact between cryptocurrencies and the stock market. Kaiser and Stöckl (2020) introduce the concept of beta herding to the debate of herding, providing further robustness to their results. They also suggest Bitcoin as a ‘transfer currency,’ and show experimentally that herding measures focused on such a transfer currency give a more exact depiction of dispersion in investors’ opinions on the cryptocurrency market. By managing to extract herding tendencies based on the cross-sectional dispersion of individual stock betas, Júnior *et al.* (2020), demonstrate that regardless of market conditions, herding toward the market exhibits substantial movement and persistence.

Price dynamics of cryptocurrencies are influenced by the interaction between behavioural factors behind investor decisions and publicly accessible data flows Gurdgiev and O'Loughlin (2020). Their results show that investor sentiment can predict the price direction of cryptocurrencies, indicating direct impact of herding and anchoring biases. Furthermore, with their analysis they introduce a new paradigm for analysing behavioural drivers of the cryptocurrency assets based on the use of natural language AI to extract better quality data on investor sentiment. On a similar aspect of the literature on herding Haryanto *et al.* (2020) using trade round-trip and survival analysis, show that the cryptocurrency market exhibits a reverse disposition effect in bullish periods and the usual positive disposition effect in bearish periods. King and Koutmos (2021) examines the extent to which herding, and feedback trading behaviours drive price dynamics across nine major cryptocurrencies, documenting heterogeneity in the types of feedback trading strategies investors utilize across markets. The results indicate that some cryptocurrency markets show evidence of herding, agreeing essentially with the views of previous similar studies and offering an updated view on the issue. In their study Omane-Adjepong *et al.* (2021) examine herding in the most liquid cryptocurrency markets relative to traditional financial markets of 10 emerging economies within the G20. Their results reference significant symmetric crowd and imitation trading, which are dependent on time. Additionally, they report asymmetric herd behaviour in the cryptocurrency and stock markets, indicative that traders of these markets react collectively to extreme return movement with implied high risk and consequences for market informational efficiency. Manahov (2021) utilising millisecond data for five major cryptocurrencies, and two cryptocurrency indices [Crypto Index (CRIX) and CCI30 Crypto Currencies Index], investigates the relationship between cryptocurrency liquidity, herding behaviour and profitability during periods of extreme price movements (EPMs). The results of the study demonstrate that cryptocurrency traders facilitate EPMs and demand liquidity even during the utmost EPMs, observing the presence of herding behaviour during up markets across the entire dataset. Ren and Lucey (2022) investigate herding behaviour among two types of cryptocurrencies based on their energy usage ("black/dirty" and "green/clean").

Their results show that herding is present only in the “black/dirty” market and is even more pronounced during periods of down markets. Furthermore, they show that “green/clean” cryptocurrencies herd with “black/dirty” cryptocurrencies when both markets are positive. Choi *et al.* (2022) using hourly data for eight major cryptocurrencies investigated the presence of herding, finding anti-herding behaviour at shorter time intervals and herding during longer periods, with the phenomenon being even stronger in the latter during down markets. In their study Raimundo Júnior *et al.* (2022) reveal that herding toward the market shows significant movement, and persistence regardless of the market condition. Finally, Blasco *et al.* (2022) analyse herding behaviour among exchanges around the expiration of Bitcoin futures traded on the Chicago Mercantile Exchange (CME), finding that herding appears to be significant during the week before expiration.

2.2 No Herding

Panel B of Table 1 showcases the studies whose empirical findings indicate that herding is not present among cryptocurrencies, or its effect is not clearly pronounced. On that note, the analysis of Kurt Gümüş *et al.* (2019) focuses on the cryptocurrency index and cryptocurrencies, which have existed since the arbitrarily set starting date of the CCI 30 Index. The results of the study indicate no evidence of herding behaviour in the cryptocurrency market in both CSSD and CSAD approaches. Furthermore, Coskun *et al.* (2020), studied the impact of economic policy uncertainty on herding behaviour in addition to the CSAD approach. Using daily data from the 14 most popular cryptocurrencies, the findings for the entire sample point to anti-herding behaviour. Additionally, during the ‘up and down’ market phases, there was no notable asymmetric behaviour. Building up on previous research Amirat and Alwafi (2020), utilised data from 20 major cryptocurrencies and MV Index Solution Crypto Compare Digital Assets for large cap index. The authors state that no indication of herding tendency was present in the results when using the cross-sectional absolute standard deviation method. However, by utilising a rolling window approach, the data reveal considerable herding behaviour that fluctuates across time. Finally, the study discovers an inverse link between herding behaviour and the Bloomberg consumer comfort index, implying that when traders feel uneasy, they prefer to ignore their expectations and focus on market performance.

2.3 Herding in cryptocurrencies during the pandemic

The recent COVID-19 pandemic, as a textbook case of an exogenous shock, posed the question of whether herding behaviour is present in the cryptocurrency market mid the COVID-19 pandemic. One of the first papers examining herding behaviour during COVID-19 is that of Mnif *et al.* (2020), who, using the fractal theory and analysing daily returns of five cryptocurrencies, find that all, except for Bitcoin, become more efficient in the post-COVID-19 period; that is, less herding behaviour exists after the pandemic. In addition, Yarovaya *et al.* (2021) examining the most traded cryptocurrency markets, find that although the COVID-19 pandemic increased the volatility in cryptocurrency markets, it does not seem to cause stronger herding in these markets.

On the other hand, the analysis of Susana *et al.* (2020) revealed that herding was present among all cryptocurrencies of the sample in normal conditions, but not during market upswing or downswing. Mandaci and Cagli (2022), employing a novel Granger causality methodology with a Fourier approximation, find significant herding behaviour during the COVID-19 outbreak, while Lee *et al.* (2021) and Shrotryia and Kalra (2021), find that herding effect is present, only during down markets in periods of high volatility and up markets in periods of low volatility, and during normal, bullish and high volatility periods accordingly. Finally, in their study, Rubbaniy *et al.* (2021), utilise over 100 cryptocurrencies in order to investigate the phenomenon. Their empirical results reveal the presence if herding behaviour during extreme market conditions, with significant herding being found during COVID-19 post-lockdowns periods.

3. Momentum and Overreaction/Reversal

Among the most classical historical anomalies being present on relatively 'immature' markets, momentum and contrarian effects stand out. In this section, we discuss the popular momentum strategy as implemented in the cryptocurrency market. Furthermore, we document the issues of reversal and overreaction as documented in the relevant literature. Table 2 presents the set of studies that investigate the above-mentioned topics. On the issue of overreaction, Chevapatrakul and Mascia (2019) examined for the very first time the persistence of returns on Bitcoin at different parts on the return distributions through the use of the quantile autoregressive (QAR) models. According to the authors, lower quantiles of the daily return distribution and upper quantiles of the weekly return distribution show positive correlation with historical returns, indicating overreaction in the Bitcoin market. In their study, Kosc *et al.* (2019) report the results of investigation of the momentum and contrarian effects on cryptocurrency markets, with the investigated investment strategies involving 100 cryptocurrencies with the largest market cap. Their empirical results show a clear and significant dominance of the short-term contrarian effect over both momentum effect and the benchmark portfolios, along with a significant diversification potential for all cryptocurrency portfolios with relation to the S&P500 index. Similarly, the findings of Begušić and Kostanjčar (2019) show a substantial momentum impact in the most liquid cryptocurrencies, corroborating investor herding hypotheses. Furthermore, the authors suggest two advantageous long-only strategies: illiquid losers and liquid winners, both of which outperform the market capitalization weighted portfolio in terms of risk adjusted performance.

****** Table 2 ******

Caporale and Plastun (2020), extending their analysis (Caporale and Plastun, 2019), investigate if there is a momentum impact in the cryptocurrency market after one-day anomalous returns. The findings of their study show that hourly returns on positive/negative anomalous returns during the day are considerably higher/lower than on a typical positive/negative day. Liu *et al.* (2020), investigating a collection of 78 cryptocurrencies, identify three common risk factors in the returns on cryptocurrencies, which are related to cryptocurrency market return, market capitalization (size) and momentum of cryptocurrencies. The authors find that there are anomalous returns that decrease with size and increase with return momentum, and the momentum effect is more significant in small cryptocurrencies. Chu *et al.* (2020) with their findings indicate that the momentum method has the potential to be utilised successfully for bitcoin trading at a high frequency, while the study of Borgards (2021) compares the momentum impact of twenty cryptocurrencies to the stock market in the United States and finds evidence that high percentage of asset classes' creation phases are followed by momentum periods, indicating that the momentum effect is robust. It also identifies important price levels during structural components of the momentum period, when volatility spikes quickly but intensely, resulting in a price impulse in the momentum's direction. Additionally, Jia *et al.* (2022) introduce and test a three-factor pricing model including market, size, and momentum factors, outperforming relevant models suggested in the literature. On the other hand, Grobys and Sapkota (2019) retrieving a set of 143 cryptocurrencies. However, their findings, in contrary to earlier studies, do not indicate any evidence of significant momentum payoffs, supporting the view that the cryptocurrency market is far more efficient than suggested. Finally, Wen *et al.* (2022), utilising high-frequency data, showcase evidence of intraday return predictability, consisting of both intraday momentum and reversal, in the cryptocurrency market.

4. Bubbles and Contagion Effects in cryptocurrency markets

In this section we discuss the presence of contagion effect in the cryptocurrency market. Table 3 summarises the set of papers discussed in this section. The investigation of such a phenomenon is important to understand in the hope that it can better explain cryptocurrencies' price volatility. Matkovskyy and Jalan (2019) in their analysis studied contagion effects between traditional financial markets, represented by five equity indices and the EUR, USD, GBP, and JPY centralized Bitcoin markets. The empirical results showcase significant contagion effects from financial to Bitcoin markets in terms of both correlation and co-skewness of market returns. Furthermore, the findings also indicate that during crisis periods, risk-averse investors exhibit the tendency to move away from risky cryptocurrency markets towards safer financial markets. Li *et al.* (2021) find that pump-and-dump schemes lead to short-term bubbles featuring dramatic increases in prices, volume, and volatility. Using a difference-in-differences approach, they provide causal evidence that pump-and-dump schemes are detrimental to the liquidity and price of cryptocurrencies. The paper of Gronwald (2021) revisits the issue of price explosiveness in cryptocurrency markets (see also Bouri *et al.*, 2018), showing that there is strong evidence of explosive periods in cryptocurrency prices, suggesting however, the term bubble should be used with more caution, since the interpretation of these explosive periods as cryptocurrency bubbles requires a sufficient understanding of the fundamental value of cryptocurrencies. Corbet *et al.* (2022), using a regime-switching skew-normal (RSSN) methodology, investigated the presence of financial contagion among several important

Chinese stock indices during the COVID-19 pandemic, with their results showcasing contagion effects.

****** Table 3 ******

5. Sentiment and Uncertainty effects

Barberis and Thaler (2003) stated that "behavioural finance has two building blocks: limits to arbitrage, which argues that it can be difficult for rational traders to undo the dislocations caused by less rational traders; and psychology, which catalogues the kinds of deviations from full rationality we might expect to see". Since Keynes (1936) there has been an increasing attention in the identification on the role that sentiment has in the decision-making process of investors in financial markets. Barberis *et al.* (1998) have identified investor sentiment as how investors form their beliefs. Therefore, sentiment in its principle is a qualitative individual's characteristic stemming from the interconnection among numerous factors, thus making it extremely difficult to identify it. For that reason, various studies have taken various approaches in order to properly understand, measure and 'quantify' it (Brown and Cliff, 2004; Corredor *et al.*, 2013; Sibley *et al.*, 2016). Table 4 presents the set of papers discussed in this section.

****** Table 4 ******

5.1 Investor Sentiment (Attention)

In the field of cryptocurrencies now, in their study, Chen *et al.* (2019) suggest a cryptocurrency-specific lexicon that may be used to assess investor emotion and forecast cryptocurrency market returns. According to their findings, investor sentiment positively predicts excess CRIX returns without significant evidence of return reversal. Furthermore, the authors also suggest that in a market dominated by noisy traders, investor mood drives price movement and that its influence is unlikely to change in the near future. Naeem *et al.* (2021) examined the predictive ability of online investor sentiment for six major cryptocurrency returns, using two proxies, the FEARS index of Da *et al.* (2015) and Twitter Happiness sentiment. Overall, based on their findings, happiness sentiment reveals to be a persistent and robust predictor for most cryptocurrency returns, with FEARS index also showing significant predictability of returns, essentially providing evidence that online investor sentiment is a significant nonlinear predictor for most major cryptocurrencies returns. Li *et al.* (2021) in their paper investigate the relationship between investor attention and the major cryptocurrency markets by wavelet-based quantile Granger causality, with the wavelet analysis illustrating the interdependence between investor attention and the cryptocurrency returns. Specifically, investor attention has a relatively stronger impact on the cryptocurrency returns in bearish markets than that in bullish markets in the short term. Finally, AlNemer *et al.* (2021) dive into examining the relationship between investor sentiment and cryptocurrency prices. For their purpose they utilise both bivariate and multivariate wavelet techniques in order to look into the investor sentiment nexus to inter-cryptocurrency pricing. Their empirical findings reveal that the Sentix Investor Confidence index is useful in understanding the long-term fluctuations of Bitcoin and Litecoin values. The analysis also shows that Bitcoin prices have a time-dependent link with other cryptocurrencies and the Sentix Investor Confidence index, which was most noticeable during the Bitcoin bubble.

5.2 Market/Public Sentiment

Garcia and Schweitzer (2015) present a consistent method to the creation of algorithmic traders that incorporates multiple data sources, such as economic indications of volume and price of exchange for USD, adoption of Bitcoin technology, and Bitcoin transaction volume. According to the findings of their analysis, rising Bitcoin prices are preceded by growing opinion polarisation and exchange volume, while rising emotional valence is preceded by rising opinion polarisation and exchange volume. The study of Demir *et al.* (2018) examines the economic policy uncertainty (EPU) index's predictive power on daily Bitcoin returns, demonstrating that the EPU has predictive power on Bitcoin returns. The research reveals that Bitcoin returns are essentially inversely related to the EPU. However, for both the lower and higher quantiles of Bitcoin returns and the EPU, the effect is positive and substantial. Advancing the level of understanding on cryptocurrencies and public sentiment Ayvaz and Shiha (2018) used lexicon-based sentiment analysis techniques to explore the relationship between public sentiments on social media regarding cryptocurrencies and price fluctuations, with the objective of determining the feasibility of forecasting cryptocurrency values. Their findings show that utilising lexicon-based sentiment analysis approaches to forecast Bitcoin price fluctuations is unreliable. The research of Gurdgiev *et al.* (2019) focuses on how sentiment analysis may be used to estimate the impacts of four distinct types of attitudes toward cryptocurrency marketplaces in order to forecast price movement, while Baig *et al.* (2019) seek to explain the unusual level of Bitcoin price clustering using various measures of Bitcoin-level and market-wide sentiment, with their empirical results suggesting that sentiment has a strong positive association with price clustering. Anastasiou *et al.* (2021) examine the effect of crisis sentiment on cryptocurrencies' price crash risk utilising the FEARS index. The authors showed that cryptocurrencies' price crash risk is positively related to the FEARS index, indicating that a higher crisis sentiment by investors increases cryptocurrencies' price crash risk, and their findings advancing the understanding of the consequences of sentiment on the cryptocurrency market. Finally, Anamika and

Subramaniam (2022) examine the influence of investor sentiment based on news headlines, finding that indeed there is a significant impact in cryptocurrency returns.

5.3 Search Volume Predictability

During the past decade, there has been an emphasis on the utility of search volume data in finance and the increasingly usefulness of such a proxy for the definition of both economic and non-economic variables. Google search data make it possible to directly and objectively reveal an individual's sentiments. According to statcounter.com, by July 2020, it accounted for 92.17% worldwide. One of the first empirical studies, introducing Google search data, is the analysis by Ginsberg *et al.* (2009) who used relevant data to predict influenza epidemics before their official listing. In the field of economics, Da *et al*. (2011) proposed in their analysis the use of search volume data in order to measure an investors' attention, Choi and Varian (2012) attempted to predict claims for unemployment benefits by utilizing Google search data, Bank *et al.* (2011) showed that Google search volume not only serves as an intuitive proxy for overall firm recognition, but also captures the attention of stock market investors and Takeda and Wakao (2014) studied the relationship between the stock-trading volume of Japanese stocks and Google search intensity.

Moving now closer to our work and to the cryptocurrency related literature, Kristoufek (2013) in his study analysed the connection between Google search, Wikipedia and Bitcoin price data, finding that increased interest in Bitcoin leads to higher prices, which subsequently results back into even higher search volume. Similarly, Garcia *et al.* (2014) identify two feedback loops, one driven by word of mouth, and the other by new Bitcoin adopters, that lead public interest towards price bubbles. As they state in their analysis both these loops suggest that individual investors satisfy their information demand using Google or Wikipedia which then leads to trading activity in Bitcoin. However, Garcia and Schweitzer (2015), in their related study, contradict the results of Kristoufek (2013) stating that the search volume variable carries no information which is useful as a trading signal. Additionally, Urquhart (2018) examines the connection among Google search data and Bitcoin returns/volume, finding that searches do not seem to serve as a suitable volatility predictor. Two other worth mentioning studies are these of Panagiotidis *et al.* (2019) and Bleher and Dimplf (2019). Specifically, Panagiotidis *et al.* (2019) showed evidence that gold and search intensity are the most important drivers of Bitcoin returns, while Bleher and Dimplf (2019) evaluated the usefulness of Google search data in predicting returns and volatility of cryptocurrencies. Their results, being in line with the relevant literature on financial markets, indicate that returns are not predictable while volatility is predictable to some extent. Finally, Guégan and Renault (2021) use a dataset of approximately one million messages sent on StockTwits to explore the relationship between investor sentiment on social media and intraday Bitcoin returns. They find a statistically significant relationship between investor sentiment and Bitcoin returns for frequencies of up to 15 minutes.

6. Investment Decision-Making

In this section we discuss the related studies dealing with the impact of behavioural finance elements on cryptocurrency investment decisions, optimism bias, disposition, lottery and size effect. Table 5 presents the set of studies that investigate the above-mentioned topics. Zhang *et al.* (2019), investigate whether Chinese cryptocurrency investors show confirmatory bias when processing authority-related news. By using data from the largest cryptocurrency exchange in China, the study finds that investors' response to authority-related news is negative and statistically significant. Moreover, the authors find that the abnormal trading volume and standard deviation of abnormal trading volume are significantly higher for authority-related news with higher readability, suggesting investors respond to the more readable authority-related news with more trading behaviour. Al-Mansour (2020) investigates the impact of behavioural finance elements on cryptocurrency investment decisions, focusing on Arab investors who participate in the cryptocurrency market. A quantitative technique was utilised, with 112 questionnaires sent using a snowball sample method. The findings of the study demonstrate that herding theory, prospect theory, and heuristic theory have a substantial impact on investors' Bitcoin investing decisions. Finally, Luo *et al.* (2021) introduce a behavioural channel to argue that the degree of ambiguity aversion is a prominent source of abnormal returns from investment in Bitcoin markets. Using data over a ten-year period, they show that Bitcoin investors exhibit, on average, an increasing aversion to ambiguity. Furthermore, investors are found to earn abnormal returns only when ambiguity is low.

****** Table 5 ******

6.1 Optimism bias

On the issue of optimism bias, Caferra (2020) investigates the link between news-driven feelings and behaviour convergence in the cryptocurrency market. The results showcase that the peaks and falls of optimism determine returns variability using both cross-sectional standard (CSSD) and absolute (CSAD) deviation. Indeed, the research further shows that an increase in news positivity is related with a reduced returns dispersion, demonstrating investor convergence. The study of Hidajat (2019) tried to fill the research gap on cryptocurrencies from the behavioural perspective. It offers a conceptual model for understanding the behavioural bias (i.e., optimism, overconfidence) being present when investing in cryptocurrencies. The study ultimately implies that prices and Bitcoin transactions are more determined by psychological factors. Building up on that Aloosh and Ouzan (2020) use behavioural economics to examine the dynamics of Bitcoin pricing. Participants in the cryptocurrency market appear to be acting irrationally. The study shows that the cryptocurrency market has a significant small price bias, which supports the idea that investors respond to news differently depending on the price level. Ultimately, the authors showcase that low-priced cryptocurrencies are much more volatile than their high-priced counterparts.

6.2 Disposition effect

The research paper of Castro (2019) aims to study irrational behaviour with a focus on the disposition effect in stocks and Bitcoin. The results of the study's investigation show that although indeed there is disposition effect in Bitcoin, it is proven to be much stronger for stocks. Cao and Rhue (2019) in their analysis ask whether the presence and news sentiment from prestigious business journals would affect the Bitcoin return. Using a bag-of-words model and a dictionary-based approach, they calculate the sentiment embedded in the news headlines, and estimate a regression of financial news sentiment on Bitcoin daily return. They find that positive sentiment contributes significantly negatively to Bitcoin return on the same day (negative sentiment day contributes positively, although not significantly). Authors state that these findings extend the understanding of disposition effect to the cryptocurrency market. Haryanto *et al.* (2020) investigate the disposition effect using the Mt. Gox data between 2011–2013. Using trade round-trip and survival analysis, the analysis reveals that the cryptocurrency market exhibits a reverse disposition effect in bullish periods and the usual positive disposition effect in bearish periods. In their paper Schatzmann and Haslhofer (2020) expand on existing research and empirically investigate the prevalence of the disposition effect in Bitcoin. Their results show that investors are indeed subject to the disposition effect, tending to sell their winning positions too soon and holding on to their losing position for too long. As stated in their analysis, this effect is very prominently evident from the boom-and-bust year 2017 onwards, confirmed via most of the applied technical indicators.

6.3 Lottery effects

Grobys and Junttila (2021) explore lottery-like demand in cryptocurrency markets. Their results suggest that parallel to stock markets, similar behavioural mechanisms of underlying investor behaviour are present also in new virtual currency markets. Lin *et al.* (2021) construct the lottery-like portfolio based on the maximum return. Their results showcase a lottery-like momentum, meaning that a higher maximum return leads to a higher future return among 64 cryptocurrencies. The analysis of Li *et al.* (2021) studies the MAX effect in the cryptocurrency due to its lottery-like features (i.e., large positive skewness). Contrary to findings in other markets, this study demonstrates that cryptocurrencies with higher maximum daily returns tend to achieve higher returns in the future and call this the "MAX momentum" effect. Furthermore, the authors showcase that a variation exists in the magnitude of the MAX momentum effect depending on market conditions, investor sentiment and the under-pricing of cryptocurrencies. Finally, Ozdamar *et al.* (2021) provide evidence for a positive and statistically significant relationship between the maximum daily return within the previous month (MAX) and the expected returns on cryptocurrencies. Their univariate portfolio analysis shows that weekly average raw and risk-adjusted return differences between portfolios of cryptocurrencies with the highest and lowest MAX deciles are 3.03% and 1.99%, respectively, with the results being robust with respect to the differences in size, price, momentum, short-term reversal, liquidity, volatility, skewness, and investor sentiment.

6.4 Size effects

Ultimately, Li *et al.* (2020) examine the size effect in the cryptocurrency market with a sample of more than 1800 cryptocurrencies. The authors of this research find that cryptocurrencies with small market value tend to perform better in the future, which challenges the Efficient Market Hypothesis. The size effect is found to be stable over the sample period and robust to the sample size.

7. Conclusions

In the past decade, cryptocurrencies have emerged as new asset class, gathering both investors' funds and the attention of the academic community. As a result, the literature on cryptocurrencies and issues apt to behavioural finance has been consistently growing, moving in tandem with the increasing market capitalisation and trading volumes of the cryptocurrency market. This paper offers a comprehensive review of the related literature, highlighting the main empirical findings regarding herding behaviour among cryptocurrencies, momentum effects and overreaction, contagion effect, sentiment (investor's, market's) and uncertainty, along with studies related to investment decision making, optimism bias, disposition, lottery and size effect.

Innovative financial assets like cryptocurrencies, represent a big challenge for the area of behavioural finance and financial economics in general, since there are fundamental elements of difference both on the manner of how this market operates, but also on the 'architecture' of cryptocurrencies. For example, when compared to traditional markets, in the cryptocurrency market there exists a total lack of an 'anchor' in terms of linkage to some real tangible value. So, identifying the factors and properties that define these innovative assets will be of utmost importance. Therefore, in terms of potential future research, the need for taking into account the technical elements of cryptocurrencies (i.e., cryptocurrency/blockchain design) will become more and more pronounced. In addition, the use of high-frequency data could potentially help answering questions that are still debated among academics. Finally, future studies on the behavioural aspects of the cryptocurrency market could concentrate on further exploring the possible interrelationship between cryptocurrencies and traditional financial markets.

References

Al-Mansour, B.Y., 2020. Cryptocurrency Market: Behavioral Finance Perspective. The Journal of Asian Finance, Economics and Business 7, 159–168.

AlNemer, H.A., Hkiri, B., Khan, M.A., 2021. Time-Varying Nexus between Investor Sentiment and Cryptocurrency Market: New Insights from a Wavelet Coherence Framework. Journal of Risk and Financial Management 14, 275.

Aloosh, A., Ouzan, S., 2020. The psychology of cryptocurrency prices. Finance Research Letters 33, 101192.

Amirat, A., Alwafi, W., 2020. Does herding behavior exist in cryptocurrency market? Cogent Economics & Finance 8, 1735680.

Anamika, A., Subramaniam, S., 2022. Do news headlines matter in the cryptocurrency market? Applied Economics 0, 1–17.

Anastasiou, D., Ballis, A., Drakos, K., 2021. Cryptocurrencies’ Price Crash Risk and Crisis Sentiment. Finance Research Letters 101928.

Ayvaz, S., Shiha, M.O., 2018. A Scalable Streaming Big Data Architecture for Real-Time Sentiment Analysis, in: Proceedings of the 2018 2nd International Conference on Cloud and Big Data Computing, ICCBDC’18. Association for Computing Machinery, New York, NY, USA, pp. 47–51.

Ballis, A., Drakos, K., 2020. Testing for herding in the cryptocurrency market. Finance Res. Lett. 33, 101210.

Ballis, A., Drakos, K., 2021. The Explosion in Cryptocurrencies: A Black Hole Analogy. Financial Innovation 7, 8.

Baig, A., Blau, B.M., Sabah, N., 2019. Price clustering and sentiment in bitcoin. Finance Research Letters 29, 111–116.

Bank, M., Larch, M., & Peter, G., 2011. Google search volume and its influence on liquidity and returns. Financial Markets and Portfolio Management, 25(3), 239–264.

Barberis, N., Shleifer, A., & Vishny, R., 1998. A model of investor sentiment. Journal of financial economics, 49(3), 307-343. https://doi.org/10.1016/S0304-405X(98)00027-0

Barberis, N., & Thaler, R., 2003. A survey of behavioral finance. Handbook of the Economics of Finance 1, 1053-1128.

Begušić, S., Kostanjčar, Z., 2019. Momentum and liquidity in cryptocurrencies.

Bikhchandani, S. and Sharma, S., 2001. Herd Behavior in Financial Markets. IMF Staff Papers, International Monetary Fund, 47, 279–310.

Blasco, N., Corredor, P., Satrústegui, N., 2022. The witching week of herding on bitcoin exchanges. Financ Innov 8, 26.

Bleher, J., Dimpfl, T., 2019. Today I got a million, tomorrow, I don't know: On the predictability of cryptocurrencies by means of Google search volume. International Review of Financial Analysis 63, 147–159.

Borgards, O., 2021. Dynamic time series momentum of cryptocurrencies. The North American Journal of Economics and Finance 57, 101428.

Bouri, E., Gupta, R., Roubaud, D., 2019. Herding behaviour in cryptocurrencies. Finance Res. Lett. 29, 216-221.

Bouri, E., Shahzad, S.J.H., Roubaud, D., 2019. Co-explosivity in the cryptocurrency market. Finance Research Letters 29, 178–183.

Brown, G.W., Cliff, M.T., 2004. Investor sentiment and the near-term stock market. Journal of Empirical Finance 11, 1–27. https://doi.org/10.1016/j.jempfin.2002.12.001

Caferra, R., 2020. Good vibes only: The crypto-optimistic behavior. Journal of Behavioral and Experimental Finance 28, 100407.

Cao, M., Rhue, L., 2019. Disposed of Bitcoin? Using the Disposition Effect to Understand Financial News Sentiment and Bitcoin Returns. AMCIS 2019 Proceedings.

Caporale, G.M., Plastun, A., 2019. The day of the week effect in the cryptocurrency market. Finance Research Letters 31.

Caporale, G.M., Plastun, A., 2020. Momentum effects in the cryptocurrency market after one-day abnormal returns. Financ Mark Portf Manag 34, 251–266.

Castro, M.A., 2019. The disposition effect in stocks versus bitcoin.

Chen, C.Y.-H., Guo, L., Renault, T., 2019. What Makes Cryptocurrencies Special? Investor Sentiment and Return Predictability (SSRN Scholarly Paper No. ID 3398423). Social Science Research Network, Rochester, NY.

Chevapatrakul, T., Mascia, D.V., 2019. Detecting overreaction in the Bitcoin market: A quantile autoregression approach. Finance Research Letters 30, 371–377.

Choi, K.-H., Kang, S.H., Yoon, S.-M., 2022. Herding behaviour in Korea's cryptocurrency market. Applied Economics 54, 2795–2809.

Choi, H., Varian, H., 2012. Predicting the present with Google Trends. Economic Record, 88, 2-9.

Chu, J., Chan, S., Zhang, Y., 2020. High frequency momentum trading with cryptocurrencies. Research in International Business and Finance 52, 101176.

Corbet, S., Hou, Y. (Greg), Hu, Y., Oxley, L., 2022. Financial contagion among COVID-19 concept-related stocks in China. Applied Economics 54, 2439–2452.

Corbet, S., Lucey, B. M., Urquhart, A., Yarovaya, L., 2019. Cryptocurrencies as a financial asset: a systematic analysis. International Review of Financial Analysis 62, 182-199.

Corredor, P., Ferrer, E., Santamaria, R., 2013. Investor sentiment effect in stock markets: Stock characteristics or country-specific factors? International Review of Economics & Finance 27, 572–591.

Coskun, E.A., Lau, C.K.M., Kahyaoglu, H., 2020. Uncertainty and herding behavior: evidence from cryptocurrencies. Research in International Business and Finance 54, 101284.

Da, Z., Engelberg, J., Gao, P., 2011. In search of attention. The Journal of Finance, 66 (5), 1461-1499.

Da, Z., Engelberg, J., Gao, P., 2015. The sum of all fears investor sentiment and asset prices. Review of Financial Studies, 28 (1), 1-32.

da Gama Silva, P.V.J., Klotzle, M.C., Pinto, A.C.F., Gomes, L.L., 2019. Herding behavior and contagion in the cryptocurrency market. Journal of Behavioral and Experimental Finance 22, 41–50.

Demir, E., Gozgor, G., Lau, C.K.M., Vigne, S.A., 2018. Does economic policy uncertainty predict the Bitcoin returns? An empirical investigation. Finance Research Letters 26, 145–149.

Garcia, D., Tessone, C.J., Mavrodiev, P., Perony, N., 2014. The digital traces of bubbles: feedback cycles between socio-economic signals in the Bitcoin economy. Journal of The Royal Society Interface 11, 20140623.

Garcia, D., & Schweitzer, F., 2015. Social signals and algorithmic trading of Bitcoin. Royal Society Open Science, 2(9).

Ginsberg, J., Mohebbi, M. H., Patel, R. S., Brammer, L., Smolinski, M. S., Brilliant, L., 2009. Detecting influenza epidemics using search engine query data. Nature, 457, 1012–1014.

Grobys, K., Junttila, J., 2021. Speculation and lottery-like demand in cryptocurrency markets. Journal of International Financial Markets, Institutions and Money 71, 101289.

Grobys, K., Sapkota, N., 2019. Cryptocurrencies and momentum. Economics Letters 180, 6–10.

Gronwald, M., 2021. How explosive are cryptocurrency prices? Finance Research Letters 38, 101603.

Guégan, D., Renault, T., 2021. Does investor sentiment on social media provide robust information for Bitcoin returns predictability? Finance Research Letters 38, 101494.

Gurdgiev, C., O'Loughlin, D., 2020. Herding and anchoring in cryptocurrency markets: Investor reaction to fear and uncertainty. Journal of Behavioral and Experimental Finance 25, 100271.

Gurdgiev, C., O'Loughlin, D., Chlebowski, B., 2019. Behavioral Basis Of Cryptocurrencies Markets : Examining Effects Of Public Sentiment, Fear, And Uncertainty On Price Formation. Journal of Financial Transformation 49, 110–121.

Haryanto, S., Subroto, A., Ulpah, M., 2020. Disposition effect and herding behavior in the cryptocurrency market. J. Ind. Bus. Econ. 47, 115–132.

Hidajat, T., 2019. BEHAVIOURAL BIASES IN BITCOIN TRADING. Fokus Ekonomi : Jurnal Ilmiah Ekonomi 14, 337–354.

Jalal, R.N.-U.-D., Sargiacomo, M., Sahar, N.U., Fayyaz, U.-E.-R., 2020. Herding Behavior and Cryptocurrency: Market Asymmetries, Inter-Dependency and Intra-Dependency. The Journal of Asian Finance, Economics and Business 7, 27–34.

Jia, B., Goodell, J.W., Shen, D., 2022. Momentum or reversal: Which is the appropriate third factor for cryptocurrencies? Finance Research Letters 102139.

Júnior, G. de S.R., Palazzi, R.B., Tavares, R. de S., Klotzle, M.C., 2020. Market Stress and Herding: A New Approach to the Cryptocurrency Market. Journal of Behavioral Finance 0, 1–15.

Kaiser, L., Stöckl, S., 2020. Cryptocurrencies: Herding and the transfer currency. Finance Research Letters 33, 101214.

Kallinterakis, V., Wang, Y., 2019. Do investors herd in cryptocurrencies – and why? Research in International Business and Finance 50, 240–245.

Keynes, J. M., 1936. The general theory of employment, interest and money. New York: Harcourt, Brace.

King, T., Koutmos, D., 2021. Herding and feedback trading in cryptocurrency markets. Ann Oper Res 300, 79–96.

Kosc, K., Sakowski, P., Ślepaczuk, R., 2019. Momentum and contrarian effects on the cryptocurrency market. Physica A: Statistical Mechanics and its Applications 523, 691–701.

Kristoufek, L., 2013. BitCoin meets Google Trends and Wikipedia : Quantifying the relationship between phenomena of the Internet era. Sci Rep 3, 3415.

Kumar, A., 2020. Empirical investigation of herding in cryptocurrency market under different market regimes. Review of Behavioral Finance ahead-of-print.

Kurt Gümüş, G., Gümüş, Y., Çimen, A., 2019. Herding Behaviour in Cryptocurrency Market: CSSD and CSAD Analysis, in: Hacioglu, U. (Ed.), Blockchain Economics and Financial Market Innovation: Financial Innovations in the Digital Age, Contributions to Economics. Springer International Publishing, Cham, pp. 103–114.

Kyriazis, N.A., 2020. Herding behaviour in digital currency markets: An integrated survey and empirical estimation. Heliyon 6, e04752.

Lee, Y.-H., Hay, C., Liu, H.-C., Diaz, J.F., 2021. Further Evidence of Herding Behavior in Cryptocurrency Markets During the COVID-19 Pandemic. Journal of Accounting, Finance & Management Strategy 16, 151–170.

Li, R., Li, S., Yuan, D., Zhu, H., 2021. Investor attention and cryptocurrency: Evidence from wavelet-based quantile Granger causality analysis. Research in International Business and Finance 56, 101389.

Li, T., Shin, D., Wang, B., 2021. Cryptocurrency Pump-and-Dump Schemes (SSRN Scholarly Paper No. ID 3267041). Social Science Research Network, Rochester, NY.

Li, Y., Zhang, W., Xiong, X., Wang, P., 2020. Does size matter in the cryptocurrency market? Applied Economics Letters 27, 1141–1149.

Li, Y., Urquhart, A., Wang, P., Zhang, W., 2021. MAX momentum in cryptocurrency markets. International Review of Financial Analysis 77, 101829.

Lin, C.-H., Yen, K.-C., Cheng, H.-P., 2021. Lottery-like momentum in the cryptocurrency market. The North American Journal of Economics and Finance 58, 101552.

Liu, W., Liang, X., Cui, G., 2020. Common risk factors in the returns on cryptocurrencies. Economic Modelling 86, 299–305.

Luo, D., Mishra, T., Yarovaya, L., Zhang, Z., 2021. Investing during a Fintech Revolution: Ambiguity and return risk in cryptocurrencies. Journal of International Financial Markets, Institutions and Money 73, 101362.

Manahov, V., 2021. Cryptocurrency liquidity during extreme price movements: is there a problem with virtual money? Quantitative Finance 21, 341–360.

Mandaci, P., Cagli, E.C., 2022. Herding intensity and volatility in cryptocurrency markets during the COVID-19. Finance Research Letters 102382.

Matkovskyy, R., Jalan, A., 2019. From financial markets to Bitcoin markets: A fresh look at the contagion effect. Finance Research Letters 31, 93–97.

Mnif, E., Jarboui, A., Mouakhar, K., 2020. How the cryptocurrency market has performed during COVID 19? A multifractal analysis. Finance Research Letters 36, 101647.

Naeem, M.A., Mbarki, I., Shahzad, S.J.H., 2021. Predictive role of online investor sentiment for cryptocurrency market: Evidence from happiness and fears. International Review of Economics & Finance 73, 496–514.

Naeem, M.A., Mbarki, I., Suleman, M.T., Vo, X.V., Shahzad, S.J.H., n.d. Does Twitter Happiness Sentiment predict cryptocurrency? International Review of Finance n/a.

Omane-Adjepong, M., Alagidede, I.P., Lyimo, A.G., Tweneboah, G., 2021. Herding behaviour in cryptocurrency and emerging financial markets. Cogent Economics & Finance 9, 1933681.

Ozdamar, M., Akdeniz, L., Sensoy, A., 2021. Lottery-like preferences and the MAX effect in the cryptocurrency market. Financial Innovation 7, 74.

Panagiotidis, T., Stengos, T., Vravosinos, O., 2019. The effects of markets, uncertainty and search intensity on bitcoin returns. International Review of Financial Analysis 63, 220–242.

Panagiotidis, T., Stengos, T., Vravosinos, O., 2018. On the determinants of bitcoin returns: A LASSO approach. Finance Research Letters 27, 235–240.

Raafat, R.M., Chater, N., Frith, C., 2009. Herding in humans. Trends in Cognitive Sciences 13, 420–428.

Raimundo Júnior, G. de S., Palazzi, R.B., Tavares, R. de S., Klotzle, M.C., 2022. Market Stress and Herding: A New Approach to the Cryptocurrency Market. Journal of Behavioral Finance 23, 43–57.

Ren, B., Lucey, B., 2022. Do clean and dirty cryptocurrency markets herd differently? Finance Research Letters 47, 102795.

Rubbaniy, G., Polyzos, S., Rizvi, S.K.A., 2020. COVID-19, Lockdowns and Herding Towards a Cryptocurrency Market-Specific Implied Volatility Index (SSRN Scholarly Paper No. ID 3740575). Social Science Research Network, Rochester, NY.

Schatzmann, J.E., Haslhofer, B., 2020. Bitcoin Trading is Irrational! An Analysis of the Disposition Effect in Bitcoin. arXiv:2010.12415 [cs, econ, q-fin].

Shrotryia, V.K., Kalra, H., 2021. Herding in the crypto market: a diagnosis of heavy distribution tails. Review of Behavioral Finance ahead-of-print.

Sibley, S.E., Wang, Y., Xing, Y., Zhang, X., 2016. The information content of the sentiment index. Journal of Banking & Finance 62, 164–179.

Susana, D., Kavisanmathi, J.K., Sreejith, S., 2020. Does Herding Behaviour Among Traders Increase During Covid 19 Pandemic? Evidence from the Cryptocurrency Market, in: Sharma, S.K., Dwivedi, Y.K., Metri, B., Rana, N.P. (Eds.), Re-Imagining Diffusion and Adoption of Information Technology and Systems: A Continuing Conversation, IFIP

Advances in Information and Communication Technology. Springer International Publishing, Cham, pp. 178–189.

Takeda, F., Wakao, T., 2014. Google search intensity and its relationship with returns and trading volume of Japanese stocks. Pacific-Basin Finance Journal, 27, 1-18.

Urquhart, A., 2018. What causes the attention of Bitcoin? Economics Letters 166, 40–44.

Vidal-Tomás, D., Ibáñez, A.M., Farinós, J.E., 2019. Herding in the cryptocurrency market: CSSD and CSAD approaches. Finance Research Letters 30, 181–186.

Wen, Z., Bouri, E., Xu, Y., Zhao, Y., 2022. Intraday return predictability in the cryptocurrency markets: momentum, reversal, or both (SSRN Scholarly Paper No. 4080253). Social Science Research Network, Rochester, NY.

Yarovaya, L., Matkovskyy, R., Jalan, A., 2021. The effects of a "black swan" event (COVID-19) on herding behavior in cryptocurrency markets. Journal of International Financial Markets, Institutions and Money 75, 101321.

Zhang, S., Zhou, X., Pan, H., Jia, J., 2019. Cryptocurrency, confirmatory bias and news readability – evidence from the largest Chinese cryptocurrency exchange. Accounting & Finance 58, 1445–1468.

Tables

Table 1: Herding related literature.

	Main Findings
Panel A: Herding Behaviour	
Ballis and Drakos (2020)	The results provide evidence that the up-events market dispersion follows market movements at a faster pace compared to the down events.
Blasco *et al.* (2022)	The presence of herding behaviour among exchanges around the expiration of Bitcoin futures traded on the Chicago Mercantile Exchange (CME), appears to be significant during the week before expiration.
Bouri *et al.* (2019)	The findings indicate that there is considerable herding behaviour that fluctuates over time, and that herding tends to occur as uncertainty increases.
Choi *et al.* (2022)	Finding reveal anti-herding behaviour at shorter time intervals and herding during longer periods, with the phenomenon being even stronger in the latter during down markets.
Da Gama Silva *et al.* (2019)	The results revealed herding behaviour, demonstrating extreme periods of adverse herd behaviour.
Gurdgiev and O'Loughlin (2020)	Results show that investor sentiment can predict the price direction of cryptocurrencies, indicating direct impact of herding and anchoring biases
Haryanto *et al.* (2020)	Findings show that the cryptocurrency market exhibits a reverse disposition effect in bullish periods and the usual positive disposition effect in bearish periods.
Jalal *et al.* (2020)	The presence of herding is confirmed in cryptocurrencies in the upper quantiles during bullish and high volatility times due to investor overexcitement, which leads to large volume trading.
Júnior *et al.* (2020)	Results demonstrate that regardless of market conditions, herding toward the market exhibits substantial movement and persistence.
Kaiser and Stöckl (2020)	The study shows experimentally that herding measures focused on a transfer currency give a more exact depiction of dispersion in investors' opinions on the cryptocurrency market.
Kallinterakis and Wang (2019)	The results suggest that, besides herding and asymmetry (stronger during up-markets), the cryptocurrency market entails strong destabilizing potential.
King and Koutmos (2021)	Study documents heterogeneity in the types of feedback trading strategies investors utilize across markets.
Kumar (2020)	Herding is pronounced when the market is either passing through stress or has become highly volatile.
Kyriazis (2020)	The empirical estimations of the study reveal that herding behaviour is evident only in bull markets.
Manahov (2021)	The results of the study demonstrate that cryptocurrency traders facilitate EPMs and demand liquidity even during the utmost EPMs, observing the presence of herding

	behaviour during up markets across the entire dataset.
Omane-Adjepong *et al.* (2021)	Results reference significant symmetric crowd and imitation trading, which are dependent on time, along with asymmetric herd behaviour in the cryptocurrency and stock markets.
Raimundo Júnior *et al.* (2022)	Findings showcase that herding toward the market shows significant movement, and persistence regardless of the market condition.
Ren and Lucey (2022)	Results show that herding is present only in the “black/dirty” market and is even more pronounced during periods of down markets. Furthermore, they show that “green/clean” cryptocurrencies herd with “black/dirty” cryptocurrencies when both markets are positive.
Vidal-Tomás *et al*. (2019)	The smallest cryptocurrencies are herding with the largest ones
Panel B: No Herding	
Amirat and Alwafi (2020)	Results state that no indication of herding tendency was present in the results when using the cross-sectional absolute standard deviation method.
Coskun *et al.* (2020)	The findings for the entire sample point to anti-herding behaviour. Additionally, during the ‘up and down’ market phases, there was no notable asymmetric behaviour.
Kurt Gümüş *et al.* (2019)	The results of the study indicate no evidence of herding behaviour in the cryptocurrency market in both CSSD and CSAD approaches.
Panel C: Herding during the COVID-19 Pandemic	
Lee *et al.* (2021)	Find that herding effect is present, only during down markets in periods of high volatility and up markets in periods of low volatility.
Mandaci and Cagli (2022)	Findings reveal significant herding behaviour during the COVID-19 outbreak.
Mnif *et al.* (2020)	Results show that all, except for Bitcoin, become more efficient in the post-COVID-19 period; that is, less herding behaviour exists after the pandemic.
Rubbaniy *et al.* (2021)	Their empirical results reveal the presence if herding behaviour during extreme market conditions, with significant herding being found during COVID-19 post-lockdowns periods.
Shrotryia and Kalra (2021)	Herding is present during normal, bullish and high volatility periods.
Susana *et al.* (2020)	The analysis revealed that herding was present among all cryptocurrencies of the sample in normal conditions, but not during market upswing or downswing.
Yarovaya *et al.* (2021)	Findings show that although the COVID-19 pandemic increased the volatility in cryptocurrency markets, it does not seem to cause stronger herding in these markets.

Table 2: Set of studies on the topics of momentum and overreaction.

	Main Findings
Begušić and Kostanjčar (2019)	Results show a substantial momentum impact in the most liquid cryptocurrencies, corroborating investor herding hypotheses.
Borgards (2021)	Empirical results give evidence that high percentage of asset classes' creation phases are followed by momentum periods, indicating that the momentum effect is robust
Caporale and Plastun (2020)	Findings show that hourly returns on positive/negative anomalous returns during the day are considerably higher/lower than on a typical positive/negative day.
Chevapatrakul and Mascia (2019)	Lower quantiles of the daily return distribution and upper quantiles of the weekly return distribution show positive correlation with historical returns, indicating overreaction.
Chu *et al.* (2020)	Findings indicate that the momentum method has the potential to be utilised successfully for bitcoin trading at a high frequency.
Grobys and Sapkota (2019)	The findings, in contrary to earlier studies, do not indicate any evidence of significant momentum payoffs.
Jia *et al.* (2022)	The study introduced a three-factor pricing model including market, size, and momentum factors, outperforming relevant models.
Kosc *et al.* (2019)	The empirical results show a clear and significant dominance of the short-term contrarian effect over both momentum effect and the benchmark portfolios.
Liu *et al.* (2020)	Results show that there are anomalous returns that decrease with size and increase with return momentum, and the momentum effect is more significant in small cryptocurrencies.
Wen *et al.* (2022)	The findings showcase evidence of intraday return predictability, consisting of both intraday momentum and reversal, in the cryptocurrency market.

Table 3: Summarises the set of papers on bubbles and contagion effects.

	Main Findings
Corbet *et al.* (2022)	Through a regime-switching skew-normal (RSSN) methodology, results reveal that contagion effects are present among several important Chinese stock market indices during the COVID-19 pandemic.
Gronwald (2021)	The results show that there is strong evidence of explosive periods in cryptocurrency prices.
Li *et al.* (2021)	Results indicate that pump-and-dump schemes lead to short-term bubbles featuring dramatic increases in prices, volume, and volatility.
Matkovskyy and Jalan (2019)	The empirical results showcase significant contagion effects from financial to Bitcoin markets in terms of both correlation and co-skewness of market returns. Furthermore, the findings also indicate that during crisis periods, risk-averse investors exhibit the tendency to move away from risky cryptocurrency markets towards safer financial markets.

Table 4: Set of papers on sentiment and uncertainty.

	Main Findings
Panel A: Investor Sentiment (Attention)	
AlNemer *et al.* (2021)	The empirical findings reveal that the Sentix Investor Confidence index is useful in understanding the long-term fluctuations of Bitcoin and Litecoin values.
Chen *et al.* (2019)	Findings indicate that investor sentiment positively predicts excess CRIX returns without significant evidence of return reversal.
Li *et al.* (2021)	Findings show that investor attention has a relatively stronger impact on the cryptocurrency returns in bearish markets than that in bullish markets in the short term.
Naeem *et al.* (2021)	Results show that happiness sentiment reveals to be a persistent and robust predictor for most cryptocurrency returns.
Panel B: Market/Public sentiment	
Anamika and Subramaniam (2022)	Results showcase that there is a significant impact in investor sentiment and cryptocurrency returns by headline news.
Anastasiou *et al.* (2021)	Findings show that cryptocurrencies' price crash risk is positively related to the FEARS index, indicating that a higher crisis sentiment by investors increases cryptocurrencies' price crash risk.
Ayvaz and Shiha (2018)	The findings show that utilising lexicon-based sentiment analysis approaches to forecast Bitcoin price fluctuations is unreliable.
Baig *et al.* (2019)	Empirical results suggest that sentiment has a strong positive association with price clustering.
Demir *et al.* (2018)	The research reveals that Bitcoin returns are essentially inversely related to the EPU.
Garcia and Schweitzer (2015)	According to the findings of their analysis, rising Bitcoin prices are preceded by growing opinion polarisation and exchange volume, while rising emotional valence is preceded by rising opinion polarisation and exchange volume.
Gurdgiev *et al.* (2019)	The analysis shows how sentiment analysis may be used to estimate the impacts of four distinct types of attitudes toward cryptocurrency marketplaces in order to forecast price movement.
Panel C: Search Volume Predictability	
Bleher and Dimplf (2019)	The results indicate that returns are not predictable while volatility is predictable to some extent.
Garcia and Schweitzer (2015)	Study states that the search volume variable carries no information which is useful as a trading signal.
Garcia *et al.* (2014)	Results identify two feedback loops, one driven by word of mouth, and the other by new Bitcoin adopters, that lead public interest towards price bubbles.

Guégan and Renault (2021)	Empirical results indicate a statistically significant relationship between investor sentiment and Bitcoin returns for frequencies of up to 15 minutes.
Kristoufek (2013)	Findings showed that increased interest in Bitcoin leads to higher prices, which subsequently results back into even higher search volume.
Panagiotidis *et al.* (2019)	Showed evidence that gold and search intensity are the most important drivers of Bitcoin returns.
Urquhart (2018)	Analysis finds that searches do not seem to serve as a suitable volatility predictor.

Table 5: Studies dealing with the impact of behavioural finance elements on cryptocurrency investment decisions, optimism bias, disposition, lottery and size effect.

	Main Findings
Al-Mansour (2020)	The findings of the study demonstrate that herding theory, prospect theory, and heuristic theory have a substantial impact on investors' Bitcoin investing decisions.
Aloosh and Ouzan (2020)	The study shows that the cryptocurrency market has a significant small price bias, which supports the idea that investors respond to news differently depending on the price level.
Caferra (2020)	The results showcase that the peaks and falls of optimism determine returns variability using both cross-sectional standard and absolute deviation.
Cao and Rhue (2019)	They find that positive sentiment contributes significantly negatively to Bitcoin return on the same day (negative sentiment day contributes positively, although not significantly), extending the understanding of disposition effect.
Castro (2019)	The results show that although indeed there is disposition effect in Bitcoin, it is proven to be much stronger for stocks.
Grobys and Junttila (2021)	The results suggest that parallel to stock markets, similar behavioural mechanisms of underlying investor behaviour are present also in new virtual currency markets.
Haryanto *et al.* (2020)	The analysis reveals that the cryptocurrency market exhibits a reverse disposition effect in bullish periods and the usual positive disposition effect in bearish periods.
Hidajat (2019)	The analysis implies that prices and Bitcoin transactions are more determined by psychological factors.
Li *et al.* (2020)	This research finds that cryptocurrencies with small market value tend to perform better in the future.
Li *et al.* (2021)	The results demonstrate that cryptocurrencies with higher maximum daily returns tend to achieve higher returns in the future and call this the "MAX momentum" effect.
Lin *et al.* (2021)	The results showcase a lottery-like momentum, meaning that a higher maximum return leads to a higher future return among 64 cryptocurrencies.
Luo *et al.* (2021)	Results show that Bitcoin investors exhibit, on average, an increasing aversion to ambiguity. Furthermore, investors are found to earn abnormal returns only when ambiguity is low.
Ozdamar *et al.* (2021)	The analysis provides evidence for a positive and statistically significant relationship between the maximum daily return within the previous month (MAX) and the expected returns on cryptocurrencies.
Schatzmann and Haslhofer (2020)	The analysis shows that investors are indeed subject to the disposition effect, tending to sell their winning positions too soon and holding on to their losing position for too long.
Zhang *et al.* (2019)	The study finds that investors' response to authority-related news is negative and statistically significant.