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Behavioural Finance

Herding Behaviour in the Cryptocurrency Market

Nuno Lourinha Santos Ferreira Dias

Católica Porto Business School
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Resumo

Esta tese estuda a possibilidade de existência de “herding behaviour” e a sua intensidade no mercado e cryptomoedas. O estudo assume que este tipo de comportamento é um parâmetro fundamental na criação de elevado grau de volatilidade no mercado de cryptomoedas.

São analisadas através dos modelos de CSAD de Chang et al. (2000) e Chiang and Zheng (2010) oito das maiores cryptomoedas em termos de capitalização, assim como o índice CCi30, durante o período de 1º de Janeiro de 2017 até o 1º de Janeiro de 2021.

Os resultados são conclusivos, e mostram que o comportamento de “herding” está presente no mercado de cryptomoedas. Adicionalmente, o comportamento foi detetado como mais intenso durante períodos de variações positivas no mercado. A literatura revista aponta também que os investidores adotam comportamentos de “herding” de forma intencional baseados na opinião do “público” geral, sentimentos de entusiamo e de “não perder a oportunidade”.

Este tipo de comportamento é inconsistente com as teorias financeiras modernas (“Efficient Market Hypothesis”).

Palavras-chave: Finanças comportamentais, Cryptomoedas, Efficient Market Hypthesis, “Herding”, Especulação

Abstract

This thesis examines the presence and the intensity of herding behaviour in the cryptocurrency market. It approaches herding concept as a fundamental piece on explaining the price volatility observed in the cryptocurrency market.

In that sense, analysis on eight major cryptocurrencies and CCi30 index from the period of 1st of January 2017 to 1st of January 2021 was employed through the application of the CSAD models of Chang et al. (2000) and Chiang and Zheng (2010) to detect herding and its intensity across asymmetrical periods.

The results point to the existence of herding in the cryptocurrency market with a high degree of confidence. Additionally, herding was found to be more intense during upward market movements. With strong indications based on reviewed literature that investors herd intentionally based on the sentiment of the masses to not miss out on an opportunity during bullish market trends.

This type of behaviour is inconsistent with the efficiency market theory that reigns in today's financial system.

Keywords: Behavioural Finance, Cryptocurrency, Efficient Market Hypothesis, Herding, Speculation

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Chapter 1
Introduction

1.1 General background

The pillars supporting the Efficient Market Hypothesis (Fama, 1970) have become more debilitated in the sequence of financial crisis, market collapses and speculative bubbles. EMH by failing to justify these events which caused severe damage to the world's economy, highlighted the need of exploring alternative concepts (Sharma and Kumar, 2019).

Behavioural finance, for that matter, appeared as a field that is concerned with providing answers to the gaps in the modern financial theory (EMH). It explores the intricacies of human behaviour and assumes investors as not rational econometric machines ("Homo Economicus"), but as a man ("Homo Sapiens") subject to psychological biases (Thaler, 2000; Shefrin and Statman, 2011; Pompian, 2012; Barberis, 2017).

Amongst the variety of behaviours target of Behavioural Finance, herding in particular has attracted some attention. It focuses on the trading imitation between investors despite their own private information (Bikhchandani, Hirshleifer, and Welch 1992; Welch 2000; Hirshleifer and Teoh 2003; Chauhan et al., 2019). The human behavioural tendency for herding can have its origins from the lack of information or familiarity with a situation, leading often to the imitation of trades at an industry level (Bikhchandani and Sharma, 2001; Bui et al., 2018).

The main reason this behaviour has been greatly explored in this field is because it is usually linked to market anomalies such as increased and unexplained periods of high market volatility, asset prices less coherent with their fundamental value, market instability (Shiller, 1999; Javaira and Hassan, 2015) and as a possible cause for predictable economical patterns (Poincaré, 1908).

Recently behavioural finance has been exploring new market influences like automated algorithms, and networking effects linked to high frequency trading (Borch, 2016), as well as new markets such as the cryptocurrency market, which will be a central subject of this thesis.

Cryptocurrencies are an alternative technology concerned with the production, circulation and use of money through a decentralized network. Its market has seen an evolution of incredible proportions, with its global market capitalization rising from a mere 17 Billion dollars in 2017 to more than 700 Billion dollars in 2021 (source: coinmarketcap.com), and the number of cryptocurrencies also increased from over 1,000 in 2017 to more than 4,000 in 2021 (source: statista.com). Its growth is also not showing no signs of stopping, with more and more cryptocurrencies surging on a regular basis due to the openness and easiness of creation.

The cryptocurrency market is characterised to be severely connected to speculation and is often compared with the Tulip mania of the 17th and 18th century, and Bitcoin and other crypto coins volatility are said to ignore the modern financial market theorems (Taskinsoy, 2019).

The danger of the asset prices of cryptocurrencies escalating to dangerous bubbles is theorised, in this study, to be greatly influenced by herding behaviour, due to changes in the behaviour of investors and biases linked to irrationality (Bouoiyour and Selmi, 2014; Dwyer, 2015; Dyhrberg, 2016; Bukovina and Martiček, 2016) and inefficiency (Urquhart, 2016; Nadarajah and Chu, 2017), behaviour which is usually derived from rational or irrational expectations of a rapid escalation of asset prices (Brunnermeier, 2008; Evans, 1991; West, 1984). Ultimately, the aim is to prove the presence of herding in the cryptocurrency market, by analysing eight majorly capitalized crypto-coins, namely Bitcoin (BTC; 70,68%), Ethereum (ETH; 10,78%), XRP

(XRP; 1,39%), Litecoin (LTC; 1,08%), Stellar (XLM; 0,37%), Monero (XMR; 0,31%), NEM (XEM; 0,25%) and Dodge (DOGE; 0,09%)[1].

1.2 Research gaps

Although herding behaviour has been accepted as a controversial theme in the financial markets, the conclusions regarding the subject are quite disperse. Some studies find herding to be more prevalent in extreme market conditions (Christie and Huang, 1995; Zhou and Lai, 2009). While other studies suggest that herding is independent of market conditions (Hwang and Salmon, 2004). And Chang et al. (2000) documented mixed findings for a number of emerging and developed markets. So, the question of whether herding is or not independent of market conditions remains an empirical issue.

Additionally, there is the issue of difficulty in distinguishing irrational herding from the rational, because of the complexity of human behaviour. In some cases, irrational herding becomes more apparent, such as the ones observed in technology stocks that suffer a great price inflation without obvious justifying news, being for that same reason another possible future research on the subject.

When it comes to the cryptocurrency market, a few studies have been undertaken following a behavioural perspective (Nadarajah and Chu, 2017), but it is still very superficial. Further research should be conducted exploring behavioural concepts that can better explain the mechanics of this market, such as detecting herding behaviour and the feeling of investors of missing out on an opportunity. Corbet (2019) also suggests a systematic analysis of the trading efficiency of this market, which is yet to be complete, while Jalal (2020) proposes the study of interdependencies with equity market and indices as to explain what drives prices in cryptocurrencies.

[1] Source: coinmarketcap.com, 1st of January 2021

1.3 Research question

The aim of this investigation is to provide an answer to the following question:

Q_1: "Is Herding Behaviour significantly present in the Cryptocurrency Market?".

This study places the cryptocurrency market under the hypothesis that investors in the market have limited information and knowledge on how to properly evaluate these assets, and consequently rely on imitation as a form of investment strategy (herding behaviour). By first, verifying its presence a second empirical research question arises, which goes as follows:

Q_2: "Is Herding Behaviour asymmetrically intense when price of Cryptocurrencies moves up or down?".

Knowing that the cryptocurrency market has been prone to extreme price fluctuations in the past few years, and that evidence of asset bubble formation in Bitcoin (the highest capitalized crypto-coin) was verified by researchers such as Garcia et.al (2014), Godsiff (2015), Cheah and Fry (2015) and Fry and Cheah (2016), it's expectable that herding behaviour will be evident through the empirical tests of this research, as well as an asymmetric intensity of this behaviour across different periods.

1.4 Originality

In comparison to other literature on the subject, this research has a different and diversified sample of study of eight major capitalized cryptocurrencies (BTC, ETH, XRP, LTC, XLM, XMR, XEM, DOGE) and uses the CC330 index to capture the overall market evolution.

Other research uses either fewer currencies as a sample (Ajaz and Kumar, 2018; Jalal, 2020) or a broader sample in other to encompass the global cryptocurrency market behaviour (Calderón 2018; Ajaz and Kumar, 2018; Bouri, 2018) as opposed to a market index. Additionally, this research offers a more recent approach to every other research available (from the 1st of January 2017 to the 1st of January 2021), providing insights to recent events in the market.

Lastly, another key feature of this research, that distinguishes from other investigations (Ajaz and Kumar, 2018; Bouri, 2018; Jalal, 2020) is that it incorporates a review of the characteristics of the cryptocurrency market as a whole and the technology supporting each currency. This contrast brings more contextualization in comparison to most reviewed studies.

1.5 Contribution to knowledge

The study of herding behaviour in the cryptocurrency market still has a large margin for exploration, because the complexities of both these assets and human behaviour is continuously evolving. In that sense, this thesis is yet another empirical study on the subject that aims to give a better understanding of how humans and cryptocurrencies operate.

Moreover, it goes without saying that the importance of studying herding behaviour in the cryptocurrency market is largely related to the risk of markets breaking down when everyone thinks alike (Bhidé, 2010). Therefore, this study may be insightful for policymakers, because while traditional financial assets are protected and overseen by various laws against fraudulent activities, cryptocurrency markets are mostly devoid of any such control. And in an instance of a market crash, potential losses could be huge due to the skewed structure of the market (BTC market capitalization of 70%[2]). This paper might help designing firmer regulations to promote this market efficiency.

In addition, for Investors and institutional players this research can be a tool to create greater understanding of the price formation and risk structure of these assets, encouraging perhaps a reduction in the speculative traits of the currencies. For institutional and individual investors, this research could also prove to be beneficial to portfolio risk management when considering these assets, since the presence of herding in the cryptocurrency market correlated with uncertainty in the equity market could mean that investors have the portfolio diversification task more complicated when considering cryptocurrencies as an alternative investment (Dhaene et al., 2012).

For the players also referred to as "coin inventors", which can be individuals or organizations responsible for the development of the technical foundations of a cryptocurrency (European Central Bank, 2015), this research can be interesting in the sense that it can help the design of new cryptocurrency to better account for the speculative traits of the market and human sentiment.

1.6 Outline of the following chapters

The next chapter, Chapter 2, will cover first a comprehensible literature review on market efficiency, behavioural finance, and in particular herding behaviour. There will also be an overview of cryptocurrencies and its market, as well as a review of empirical tests of other studies on herding behaviour.

Chapter 3 will be composed by a presentation of the data and methodology used, followed by Chapter 4, which includes a discussion of the empirical results. The last Chapter 5 is devoted to the major conclusions drawn out from both the literature reviewed and the empirical tests.

[2] Source: coinmarketcap.com, 1st of January 2021

Chapter 2
Literature Review

2.1 Definition of Herding Behaviour in Finance

Herding in Finance dates back to 1936 when J.M. Keynes developed the renowned "General Theory". This theory assumed that professional investors followed the market to achieve an adequate investment while not being harmed in terms of their reputation. Since then, herding has been a topic greatly explored by behavioural finance in a spectrum of financial events and markets.

It is generally interpreted as any behaviour similarity or dissimilarity conveyed by the interaction of individuals (Hirshleifer and Teoh, 2003). It is believed that herding arises in a market when investors do not possess enough information or enough skills to process it, and therefore rely upon the majority of the decisions of other investors (Kumar and Goyal, 2016; Obeng, 2020).

Graham (1999) separates herding literature into four categories: informational cascades, reputational herding, investigative herding, and empirical herding.

An informational cascade in finance is seen as the process of investors that choose to ignore their own private information and instead follow the previous actions of other investors (Banerjee 1992; Bikhchandani, Hirshleifer and Welch 1992; Graham 1999; Hwang and Salmon, 2004). Cascades, as the name itself implies, assume that the initial weight of information gradually decays and therefore investors further on the chain are more likely to fall into mimicking due to the overwhelming nature of massification of beliefs. Ultimately this may lead to irregularities and inefficiencies in the markets, such as unfounded trends, booms and crashes. (Devenow, 1996; Bikhchandani, Hirshleifer and Welch 1992).

Çelen and Kariv (2004) state that there is a significant difference between informational cascades and general herding. Since the first (cascades) implies an infinite sequence of investors that ignore their own private information and become solely imitative, while the second (herding) occurs when an infinite sequence of investors make identical decisions and not necessarily while ignoring their own information. So, in a sense, not all herds are cascades.

Similar to cascades, reputational herding exists when an investor chooses to ignore their private information and imitate another investor or group of investors. This form of herding is different because of its underlying motivation, which is the positive reputational outcome obtained by the mimicking others (Trueman, 1994; Huddart, 1996). For example, asset managers in attempting to preserve their career reputation may undertake herding behaviour to protect themselves from underperformance (Scharfstein et al. 1990).

Investigative herding, on the other hand, arises when an investor chooses to investigate an information under the belief that other investors will also examine it. In this situation an investor can only collect profits if others follow the same direction and push the asset price in the direction anticipated by the investor. Otherwise, risks holding on to an asset which is not profitable (Dow and Gorton, 1994; Hirshleifer et al., 1994).

Differentiating the main motivations of herding can be quite difficult and that is not the main purpose of this thesis. Therefore, it will approach the fourth literature category emphasized by Graham as an empirical herding study. In this case, all motivations behind herding are clustered, instead of being singularly explored.

Most studies that apply clustering models suggest positive feedback investment from investors (e.g. repeat past movements) (Lakonishok et al., 1991; Nofsinger and Sias, 1999) and for this thesis the same is expected. Although, having in mind the influence of social media and internet forums as a facilitator of upward trends in the cryptocurrency market, and its history of bubble formation, from a theoretical perspective, the motivations behind herding throughout this research are expected to be comparable to an informational cascade. Where investors, like sheep, follow a particular direction, price signals or the opinions of noise traders instead of their own knowledge, where eventually the last ones on the line are victims of a market crash.

2.2 Concept of Cryptocurrencies

Cryptocurrencies are defined as a subset of digital currency denominated in their own unit of account that can be used in real economy (The World Bank, 2017). It contains a technology known as cryptography, which is a "technique" of protecting information by transforming it into an unreadable format that can only be deciphered through a secret key (European Central Bank, 2018).

The ECB (2018) divides digital currencies into three types: (i) virtual currencies that can only be used in a closed virtual software (e.g. online games); (ii) virtual currencies that are unilaterally linked to real economy, where an exchange rate exists between fiat currencies and the purchased money (e.g. Facebook Credits used to buy products online); (iii) virtual currencies that are bilaterally linked to the real economy, meaning that there are exchange rates for purchasing and selling the virtual currency. Cryptocurrencies are of the latter type. They are usually issued and controlled by their developers (ECB Virtual Currency Schemes Report, 2012).

Contrary to most definitions, the Financial Action Task Force (FATF) almost places cryptocurrencies at the same plateau of fiat currencies. Mentioning that cryptocurrencies function as a medium of exchange, unit of account and as a storage of value (characteristics of traditional money). On the other hand, FATF also mentions that cryptocurrencies do not have a legal tender status in any jurisdiction, making them a less valid form of payment in comparison.

The Body for International Settlements (BIS) and the Committee on Payments and Market Infrastructures (CPMI) qualified cryptocurrencies as assets that show features of commodities such as gold because its value is determined by the supply and demand, yet they possess zero intrinsic values. Additionally, they can be exchanged through a peer-to-peer network without any need for intermediaries.

This study interprets cryptocurrencies, similarly to most authors, as assets with a digital representation of value that aim to offer an alternative to the conventional centrally issued currencies by exploiting peer-to-peer networks and a system known as cryptography. But disagrees with the FATF perspective of placing these assets in the plateau of traditional circulating currencies, since all cryptocurrencies do not offer the same money properties and are not globally accepted as a means of exchange.

Additionally, this study agrees with CPMI that cryptocurrencies of having comparable price formation characteristics to commodities due to fixed issuing supply amounts. But mentions that supply and demand rules are not the only price drivers behind them. With technology characteristics specific to each cryptocurrency, macroeconomic and networking effects also having its important role.

2.3 Origins of modern Finance

Throughout history, mathematics, economics, and finance have had a close relationship. Finance came to a strategic point in its evolution, with the introduction of the econometrical concept of chance to market prices. This stipulates prices impossible to predict. Like Bachelier (1900) appropriately phrased, "The mathematical expectation of the speculator is zero"[3].

By 1944, the original concepts started to gain even more composure with the introduction of the "Economic Man-Statistical Man" into the equation. This Man was one that would weight potential outcomes before deciding on a move, and against uncertainties the thought process would be purely statistical (Neuman, 1944).

This view of rational participants outweighing presence in financial markets, in conjunction with the randomness of market prices and asset pricing models, gave

[3] Bachelier L. (1900), Theory of speculation, A thesis presented to the Faculty of Sciences of the Academy of Paris on March 29, 1900. Originally published in Annales de l'Ecole Normale Supérieure, 27, 21-86. Pg 10.

shape to a new (modern) interpretation, denominated as Efficient Market Hypothesis, which appeared in the 1960's and still reigns in today's financial system.

2.3.1 Efficient Market Hypothesis Theory

The Efficient Market Hypothesis, presented by Fama (1965), came to fill a void generated by scepticism around economics. The logic behind the theory was if returns were forecastable, many investors would use it to generate infinite profits (Timmerman, 2004). But since prices were random (random walk) (Samuelson, 1965), and the market was dominated by analytical investors capable of processing new information and immediately incorporate it to their beliefs, the market is efficient. From the theory perspective, investors performed choices based on rational assumption based on subjective expected utility, driving market prices closer and closer to their fundamental values (Fama, 1991).

Paradoxically and since all the information is reflected in market prices (market is efficient), this meant that even with all the advanced thinking, investors on average could only generate higher returns than the market if the intrinsic level of risk of the invested securities were higher (Fama, 1970; Malkiel, 2003).

2.3.1.1 Three forms of Market efficiency

Fama (1970) proposed three forms of market efficiency: (1) weak form, (2) semi-strong form, and (3) strong form. The first and less consistent form (weak form) aims to test how well past returns can predict future returns. Connecting to the Random Walk theory, which assumes prices to be unpredictably random, the weak form suggests technical analysis (analysis based on past performance) to be useless. The second and more robust is the semi-strong efficient market. It accepts prices to reflect both historical information and publicly available information, such as dividend pay-outs, announcements, policies, and others, meaning an investor could not outperform the market on public information alone. And finally, the strong-form presumes stock prices to fully mirror all possible information, be it public or private, becoming impossible to earn excess profits by trading on inside information (Malkiel, 2011).

2.3.1.2 Critics on the Efficient Market Hypothesis

EMH theory is largely supported by empirical evidence, but irregularities still sometimes appeared. With the financial crisis of 2008, economists questioned even further its foundations.

Fama, through all the contradicting evidence still defended his work, saying on an interview on the 28th of May of 2010 on the CNBC, that even though it is almost impossible to beat the market, it does not mean markets are always right, concluding that they cannot predict what is basically unpredictable. The author also affirmed that EMH theory for all particle purposes, works very well, subscribing to his previous defence in 1991 "The empirical literature on efficiency and asset-pricing models passes the acid test of scientific usefulness"[4]. But by convincing investors and scholars to trust the financial markets, and that prices were the reflection of all available information about securities, the theory unwillingly promoted more mindless conformism.

Justin Fox (2009)[5] stated this as the gravest sin of modern finance theory, since as an all-encompassing view over Finance, EMH is often wrong.

What Justin Fox meant was that EMH puts markets in "control" in an environment ruled by investors that systematically make errors, derived from lack of attention, emotion or insufficient knowledge. Therefore, it is important to continuously test the boundaries of this theory, so it does not become something out of superstition.

These "boundaries" are often denominated in statistics as fat tails, which are rare but significant anomalies (Shiller, 2003) incoherent with EMH. From the table 1

[4] Fama, E. (1991). Eficient Capital Markets II. Volume 46, Issue 5. Pg. 1576

[5] Fox, J. (2009). The myth of the rational market: A history of risk, reward, and delusion on Wall Street. New York: Harper Business

bellow, is possible to deduce that these exceptions to the rule are non the less extremely important, because when EMH fails, often the scale of the damage is strong.

If markets where efficient, as Fama assumes should not there be faster corrections of these events? And how come inefficiencies are spread out across markets, industries and tendentially observable through time? If not for the intervention of Behavioural Finance, which introduces not fully rational traders into the equation (Barberis, 2003), these questions would remain unexplained.

Shiller (2003) therefore, reinforces the necessity of exploring further the weakness of EMH knowing that the theory has its place in illustrating and characterizing the ideal world but cannot maintain its pure form as a describer of actual financial markets. The challenge for economists and financial players should be to incorporate Behavioural Finance as a part of their models.

EMH Irregularities	Description
Long-run Return Reversals	Tendency for overreaction and forecast ability (Debont and Thaler, 1985; Kahneman and Tversky, 1979).
Seasonal patterns	Returns from an equally weighted stock index tend to be uncharacteristically high during the first month of the year, also known as the "January effect" (Haugen and Lakonishok, 1988).
The size effect	Across long periods of time, smaller-company stocks tend to perform better then big-company stocks (Keim, 1983).
Value stocks paradigm	Stocks with low price-earnings ratio, often called "value" stocks, tend to provide better rates of return than "growth" stocks. This is consistent with behaviourists perspective that investors are overconfident in their ability to project earnings growth (Kahneman and Riepe, 1998).
Excess Volatility	Evidence of stock market prices which possess more volatility than the EMH could explain (Shiller, 2003)
Professional Investors	The Market cannot be perfectly efficient, or professional investors would not have any incentive to uncover the information (Grossman and Stiglitz, 1980).
Market Crash of 1987	"…many investors simultaneously came to believe they were holding too large a share of their wealth in risky equities." (Miller, 1991).
Dot com Bubble 1990	The internet "bubble" of the late 1990s, where exacerbated and inconsistent valuations were assigned to tech companies (Shiller, 2000).
Financial Crisis 2008	Derived from a credit boom led to irrational optimism of the borrowers, moral hazard caused by the expectation of a bailout and inefficient delays in the treatment of information, therefore increasing the "systemic risk." (Lorenzoni, 2008).

Table 1: Inefficiencies in Financial Markets. Self-elaboration

2.3.2 Behavioural Finance

Economists began to study the human nature in economics in the 1970, when models derived from investors rationalities started failing and broadly scattered and incohesive evidence was arising which seemed to be inconsistent with the rational financial theorems (Jensen, 1978 and Subrahmanyam, 2007). Psychologists have empirically shown that people calculate probabilities incorrectly. People display behaviours and psychological biases that strongly contradict the axioms of utility theory (Stanovich, 1998). And Tversky (1973) concluded that people and therefore investors rely on a limited number of heuristic principles to reduce complex tasks of assigning probabilities and predicting values to a simple judgement, which can lead to systematic errors.

With the passing of years, Behavioural Finance emerged as a science that arguments that some financial events may be understood by inputting less rational agents into models, providing theories and evidence to the reasons behind the persistent deviations from rationalities and market efficiencies (Shleifer, 2000). But this application is still not frequently applied to the current financial models, even though there are several cases that prove its usefulness.

For example, when approaching trading volumes, standard financial models typically predict very little amount of trading. Because of the assumption of rationality underling these models (both buyer and sellers are rational, so what can each party possible gain from the trade?). But in reality, millions of shares, bonds and currencies are traded daily that far surpass the standard model's predictions. Volatility is yet another example, since stock prices tend to move far more than what can be justified by changes in their fundamental value (measured by asset pricing models, that account for the present value and future dividends) (Shiller, 1981).

Additionally, the puzzling questions surrounding dividends and equity premium remain. For companies' dividends, under the assumptions of rational models, it is hard to understand why companies pay cash dividends when they are taxed a higher rate (in the US). Making little sense that company's stock price increases with the announcement of dividends, if the company will suffer higher taxes deductions (Modigliani and Miller, 1958). For equity risk premium, it is hard to explain the differential in return between treasury bills and stocks, which is too great to be explained by risk alone (Mehra and Prescott, 1985).

Finally, predictability, where efficient markets assume returns as non-forecastable of existing information, but now its agreeable that in the very least they are partially predictable on the knowledge of historical information, news and announcements. This predictability is often linked and explained by mispricing or the intrinsic risk of assets (Lakonishok et al., 1994).

These empirical facts are in many ways relevant to the better understanding of the real financial markets. Investor's behaviour often differ from what is explained in finance textbooks, then such anomalies should be considered and studied, in order to make better-informed decisions.

In addition, recently, behavioural "anomalies" have become even more evident due to the advancement of technology, where the power of social media has been associated with the mobilisation of crowds from everywhere in the world. It is clear, that new risks to the efficient functioning markets are surging, and they should also be taken seriously. This phenomenon is associated to herding behaviour, where investors are encouraged to imitate/follow the crowd not because of any fundamental pattern or news, but because other investors decisions to buy or sell.

In conclusion, behavioural finance should no longer be perceived as a controversial subject, because contrary to the Efficient Market models, which thrive on a set of simplifications and rational assumptions that are unlikely to fully explain market deviations, behavioural finance incorporates human investors behaviour and their role in driving asset prices. As Thaler stated "What other kind of finance is there?".

Dialogue Between Thaler and Fama[6]:

Thaler: "The important intellectual debate is about whether stock prices are right as opposed to whether you can beat the market".

Fama's objections, that: "without the assumptions that the prices are right, finance would get really messy".

Thaler agreed: "because human nature is a mess…It's a choice between being precisely wrong or vaguely right."

2.3.2.1 Limits to arbitrage and Cognitive psychology

Behavioural Finance is based on two cornerstones: (1) Limits to arbitrage, and (2) cognitive psychology. The first (limits to arbitrage) are supported by a series of theoretical papers showing that in markets where rational and irrational traders interact, irrationality can have a substantial and long-lived impact on prices.

It approaches the concept of arbitrage, which only exists through the Capital Asset Pricing Models (CAPMs). According to the CAPM, assets with higher risk should offer bigger compensations, otherwise exists an arbitrage opportunity present in the market (when an asset with lower risk but provides higher returns).

Limitations on arbitrage can thus be characterized as costs faced by arbitrageurs that impair them from eliminating mispricing's, leading prices further away from their fundamental values (Jensen, 1978). They choose not to take advantage of the arbitrage opportunity (Barberis, 2002) because non-fundamental demand shocks impact prices in a way arbitrage forces are no longer effective (Ritter, 2003).

Additionally, Morgenstern (1970) dispute efficiency in prices and the CAPM by showing that companies fundamental values like capital, equipment, inventories, and profits hardly fluctuate as fast and as far as stock.

[6] Fox, J. (2009). The myth of the rational market: A history of risk, reward, and delusion on Wall Street. New York: Harper Business, pg.298

Regarding the second point (cognitive psychology), behavioural finance uses experimental evidence compiled by cognitive psychologists on the biases that arise from people's beliefs and preferences (Barberis and Thaler, 2003). These biases and heuristics are viewed as one of the sources of suboptimal investment decisions and market irrationalities (Barberis, 2002).

Amongst a vast list of cognitive biases, some of the most relevant in the field of Behavioural Finance can be divided into three categories: (1) Self-Deception, (2) Heuristic Simplification, and (3) Social Interaction, reflected in the table 2 bellow.

The first category includes biases (Self-deception) relative to the feelings of investor, meaning they disregard partially or totally their statistical/rational thinking when investing which may lead to less optimal outcomes.

The second category (Heuristic simplification) translates in the way information is presented and interpreted by investors guiding them towards different conclusions and ultimately different results.

And finally, the third (Social Interaction) includes biases that are influenced by interaction between investors or entities. These biases are often mentioned to be linked to financial trends (shocks) and massification of beliefs.

Categories	**Biases**	**Concept**
Self-Deception	Overreaction	Loser portfolios outperform winner portfolios, pointing to strong evidence against market efficiency, with psychological roots.
	Overconfidence	In Finance overconfidence is the belief of investors to be above the average player in the market. A traditional illustration of overconfidence bias is the tendency to invest too much in familiar securities, even though it is a bad investment decision from the diversification point of view.
	Confirmation Bias	Happens when individuals try to justify previous ideas with preconceptions. Leaving them exposed to unforeseen events.
	Hindsight Bias	Refers to the fallacious feeling of investors, that after an event, believe they were able to predict it. It encourages a view of the world more predictable than what in really is.
	Regret Theory	An investor can be biased and discard a good investment based on a stronger expected psychological feeling of regret (Loomes, 1982 and 1987).

	Cognitive Dissonance	Konow (2000) characterizes as Cognitive Dissonance Theory, as a social-psychology theory concerned with interactions between “Cognitions”, such as beliefs, opinions, and feelings. It states when two cognitions are in conflict, exists a “Dissonance”.
Heuristic Simplification	Representativeness	Happens when individuals tend to overweight recent experiences. This bias is also known as the “law of small numbers” and assumes future patterns will resemble past ones. In Finance, for example, when returns stay high for a long period of time, investors may begin to see that as a normal phenomenon.
	Framing	Relates to the notion that individual’s interpretation changes depending how a concept is presented to them. An example of this is taken from an experiment on Medical Doctors, who make different recommendations to a patient if they see evidence presented as “survival rate” or “mortality rate”.
	Anchoring	The observed tendency in Finance is that investors would underreact to new information, but if the pattern maintains for a long enough time, they will adjust it and even perhaps overreact.
	Prospect Theory	The Prospect theory affirms that most people become less risk averse when confronted with the expectation of a financial gain, demonstrating that if investors are faced with the possibility of losing money, they usually make riskier decisions aimed at loss aversion. They tend to reverse or alter their disposition toward risk (Tversky, 1979; Kahneman, 1986; Tversky, 1992).
Social Interaction	Contagion effect	Literature defines Contagion as the international transmission of shocks, where the knowledge of a crisis in a region augments the chances of a crisis at “home” (Kaminsky, 2000). Edwards (1999), attributes Contagion only to the excess co-movement which persists after the market fundamentals and common shocks are considered. Pure contagion effects challenge the efficiency of speculative behaviour as it leads to long and excessive periods of volatility, being usually correlated with herding type of behaviour of investors.
	Herding	Herding behaviour in Finance is described as the intent of investors to copy the behaviour of other market participants (Borensztein, 2003).
	Informational Cascades	An informational cascade is described as a thought process, where an investor chooses to ignore his own private information and instead follow the common market belief, replicating the actions of other investors that acted previously (Banerjee 1992; Bikhchandani, 1992; Graham 1999).

Table 2: Taxonomy of biases. Self-elaboration.

2.3.3 Herding Behaviour

Human behaviour is not truly random. “When men are brought together, they no longer decide by chance and independently of each other but react upon one another.

Many motives may lead investors one way or the other, but there is one thing they cannot destroy, the habits they have of "Panurge's" Sheep" (Poincaré, 1908). The term "Panurge's Sheep" originates from the novel "Gargantua and Pantagrual" by François Rabelais, in which the character Panurge buys a sheep from a vendor, and having found out that he was overpriced, throws the sheep into the sea as revenge. The rest of Panurge's sheep having seen the act, quickly follow the fellow sheep, jumping as well into the sea, despite the efforts of Panurge's to stop them. This novel portrays the nature of "sheep" who instinctively and persistently follow the crowd without consideration.

This type of behaviour is also observable in humans, and in behavioural finance is also denominated as Herding Behaviour.

2.3.3.1 Spurious and Intentional Herding Behaviour

In literature, herding behaviour is often classified as two different types, Intentional or Spurious (see figure 1).

Spurious Herding can happen if investors present common factors, which may lead to a correlation in their trades, but are in fact without intent. These common factors are also called relative homogeneity, and implies similar background history between investors, such as comparable education, work experience, investment signals, and even similar regulations (De Bondt, 1997; Voronkova, 2005). Putting into a practical illustration, spurious herding could arise in the equity market if, for example, interest rates suddenly rise, and stocks become less attractive to investors. Under these modifications, participants may want to hold a smaller number of shares in their portfolio.

An investor, on the other hand, can intentionally choose to copy others because of rational or psychological reasons. One particular motivation behind such choices, is conformity, that refers to the tendency of investors to adopt others conduct based on their own convenience (Hirshleifer and Sharma, 2001).

Additionally, by communicating with others, either openly or silently (Shiller, 1995; Birkchandani et al, 1992) they may replicate another investor decision if it is believed the other investor holds better information or greater information processing skills, allowing possible benefits from imitation (Devenov, 1996; Avery 1998). This is also seen as a psychological information-based attribute of investors, that in the case of suppressing private information, can lead to a situation of informational cascades, where, through herding, prices reflect less and less information and become inefficient (Banerjee 1992, Birkchandani, 1992).

Another psychological trait displayed by financial players that may lead to intentional herding behaviour is reputation. It is recurrent in the finance professions to be subject to evaluation and judgments of other professionals, and under such conditions, worse performing individuals have an incentive to duplicate other better peers, and "free-ride" to better results (Scharfstein, 1990; Trueman, 1994). Divergently, better performing individuals can opt to follow the general public, even if it is a sub-optimal decision. They might choose to do so, if the risk of a potential failure is recognized as higher when compared to the benefits of venturing alone (Graham, 1999).

It is apparent that there are several singularities concerning herding behaviour, and empirically speaking distinguishing "spurious herding" from "intentional" herding is a difficult task, because of the multitude of motivations either rational or psychological that have the potential to affect an imitation type of behaviour in investment decisions. But that difficulty does not invalidate the importance of it.

Like Shiller (2000) brilliantly phrased "although forecasting the market is hard, and stock market bubbles tend to have some basis in economic reality, that doesn't mean they aren't bubbles, and can't cause damage when they burst "[7]. Identifying the presence and the causes of investor herding is crucial to determine possible policies to mitigate such behaviour and promote the wellbeing of the financial markets, in

[7] Quote extracted from the book: Fox, J. (2009). The myth of the rational market: A history of risk, reward, and delusion on Wall Street. New York: Harper Business, pg.259

particular intentional herding, which is usually characterized by fragility and idiosyncrasy, and may lead to excess volatility and systemic risk.

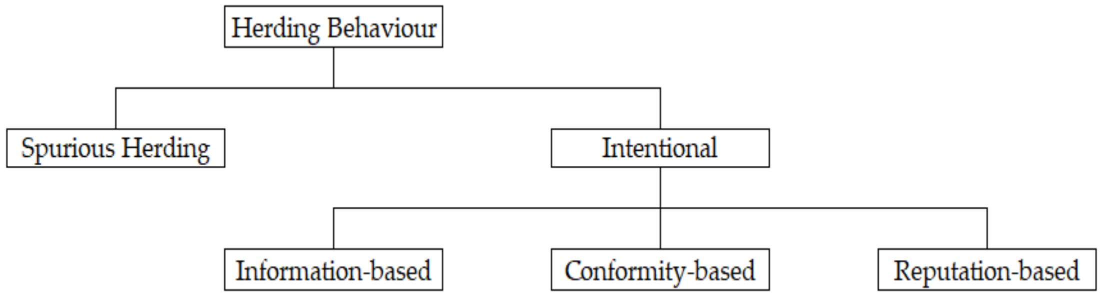


Figure 1: Types of herding. Self-elaboration.

2.3.3.2 Rational and Irrational Herding Behaviour

Through a question uttered by Alan Greenspan, former president of the Federal Reserve of United States after the financial crisis of 2008: "How do we know when irrational exuberance has unduly escalated asset values?"[8], the importance of studying herding becomes clear, since it is often quoted to have a heavy connotation with excess volatility periods, fragilization of financial markets, and financial irregularities, such as bubbles and even the aftershocks of financial crisis (Bikhchandani, 1992; Bikhchandani and Sharma, 2001).

The behaviour can surge derived from rational intentions of investors (maximization of utility; see figure 2), indicating a link between rationality and emotion, where psychological factors can optimize behaviour. For example, under asymmetric information, less-informed investors may rationally behave like price chasers (Wang, 1993).

On the other hand, herding can also have origins from an irrational, psychological perspective (Devonow, 1996; see figure 2). Pretcher (2001) infers this last perspective has a primitive instinct to survival, which results from impulsive actions from

[8] Quote extracted from the book: Fox, J. (2009). The myth of the rational market: A history of risk, reward, and delusion on Wall Street. New York: Harper Business, pg.257

observing the behaviours of others, and these impulses are normally faster than rational reflections. For example, when individual investors engage in herding as a result of irrational but systematic response to fads or sentiment (Nofsinger, 1999).

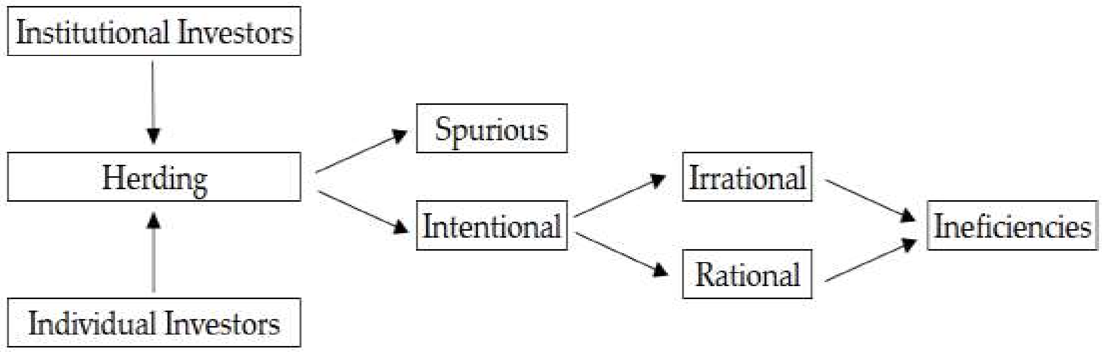


Figure 2: Taxonomy of herding behaviour. Self-elaboration.

2.4 Empirical evidence on Herding Behaviour

Herding behaviour is an endogenous factor of financial instability, and on the empirical side, the literature on the subject can be separated into two perspectives: (i) focus on the investors and financial analysis side, which portraits individual and mutual fund investors and their motivations to imitate others; (ii) focus on the overall market by using cross-sectional dispersion of asset returns methods, which examines herding from a broader perspective.

2.4.1 Evidence on individual and institutional investors

Within the first category (focus on investors and financial analysis), research tends to divide individual investors from the institutional ones, because the strength behind each of them varies.

Individual investors are generally portrayed as less informed and more prone to fads, psychological biases, informational cascades, and subject to being influenced (e.g brokerage recommendations, market gurus and forecasters), and even place too much importance on recent news (Shiller, 1984 and De Long et. al 1990).

Herding in institutions, on the other hand, is normally perceived as the primary force behind large shifts in securities' prices, although they do not necessarily implicate a destabilization of market prices.

Lakonishok, Shleifer and Vishny (1992) research points out that institutional investors are usually better informed than individual investors and are likely to herd to undervalued securities and away from overvalued ones. So implicitly herding can also move prices of securities closer to their intrinsic value.

On a contradictory note, Friedman (1984) and Dreman (1979) indicate that institutional herding, when derived from psychological biases, such as reputation, can lead to temporary price bubbles. Corresponding to Karceski (2002) study, which verified that mutual funds managers have a tendency to care more about outperforming during bull markets than underperforming in bear markets (reputational bias), increasing their demand for high beta stocks and reducing their required returns. While Richard Sias (1998) documented a stronger impact of institutional herding on prices and lower impact of herding of individuals. Additionally, he found institutional herding to be positively correlated with lag returns, which appears to be related to stock return momentum.

When comparing individual investors with institutional investors, Jensen (1968) and Gruber (1996) research affirms that mutual funds stock purchases outperform those they sell, being consistent with the hypothesis that at the margin, institutional investors are better informed than other investors.

Generally speaking, herding research on both individuals and institutions are in agreement on two aspects. One that individual investors are less informed and therefore more likely to assume herding behaviour derived from informational factors while institutions herd rationally driving market prices towards efficiency standards, or herd irrationally due to reputational standards. The second aspect that most studies are in consensus is that institutions have a stronger power to direct the market, which raises concerns relatively to irrational institutional herding.

2.4.2 Evidence on Cross-sectional dispersion methods

On the second category (herding in the overall market through the application of cross-sectional methods), there are two main models to extract evidence of herding. One devised by Christie and Hwang (1995), called cross-sectional standard deviation (CSSD) of returns. The results of using this model in the stock market usually show little evidence of herding (Christie and Hwang, 1995; Gleason 2003). Chang et.al. (2000) therefore devised a different model which is often quoted as more powerful. This model applied of a non-linear regression specification based on cross-sectional absolute deviation of returns (CSAD) which possesses a higher reach.

Tests for herding presence using this method are mixed. Chiang and Zheng (2010) study that applied the CSAD model to 25 countries and found evidence of herding in developed stock markets, with exception of the US market, in Asian markets and finally no evidence of herding in Latin American markets. Also, the results pointed to evidence of asymmetric herding in some markets especially in Asian markets where it was found to be profound and particularly during rising periods. Lindhe (2012), using similar logic to Chiang and Zheng (2010), verified the strong presence of herding in the Finnish market during large market volatility periods.

From all studies observed, herding behaviour has been found to be more pronounced during declining market conditions (Yao et al., 2013; Pochea et al. 2017; Lee, 2017), although with some exceptions. This tendency is said to be linked to the feeling of fear of investors which sell assets massively so to minimize potential losses.

2.4.3 Evidence across markets

Herding research has been conducted on a varied range of markets.

Capital markets studies, in general, find that irrational herding behaviour is more susceptible to be found during periods of financial instability. With Hirshleifer and Teoh (2003) pointing to the influence of reputational, informational factors as the possible cause. Some of the studies, indicate that herding is more visible during bullish market trends (Chiang and Zheng, 2010; Lee at al., 2013), but most point to more herding intensity on bearish stressed markets (Demirer et al., 2010; BenSaïda, 2017; Deng et al. 2018).

Additionally, herding is found to be more intense in small stock companies on periods of extreme market conditions than large stocks. Indicating that herding is also more common to "risk-lover" investors which look for large short-term returns (Lakonishok et al.,1992; Chen and Lux, 2018).

Similarly, studies regarding herding behaviour in the bond market, find the behaviour to be more intense and evident towards the riskiness intrinsic to the bonds. Meaning, lower grade bonds, that have higher illiquidity risks, show a tendency of being influenced by herding due to their use for speculation purposes (Cai et al.,2019; Chen and Ru, 2019).

Herding papers on the commodities market present conclusions that herding promotes speculative behaviour in the commodity markets. With investors being dragged towards expectations of profits in extreme conditions (Pindyck and Rotemberg, 1990; Cakan et al., 2019).

Comparably, herding in future markets is said to be influenced by the volatility of the market and more intense during periods of uncertainty, also evoking the speculation properties and sentiment of investors (McAleer and Radalj, 2013).

2.5 Context

2.5.1 Macroeconomic context from 2017 to 2021

From the year 2017 to 2021 the world economy has seen a fair share of events that greatly influenced the financial markets.

The year of 2017 was a year characterized by growth over 3%, with global robust increase in demand, reduced deflationary pressures and optimistic developments in financial markets trading. But also, uncertainties surrounding the policies stands of the new US administration following Donald Trump presidential election and their possible ramifications on the world's economy. And the same for United Kingdom after the passing vote on the Brexit in June 2016, which led to the Monetary Policy Committee to increase interest rates further (from 0,25% to 0,5%), in an attempt to normalize UKs' economy. Contrary to most expectations, knowing the many uncertainties throughout the year in major economies (US and UK), the fear indicator (VIX) remained at record lows due to the lack of volatility.

The US capital markets showed rising sings with the Dow Jones Industrial Average, S&P500 index and Nasdaq reaching new heights.

Concerning cryptocurrencies, 2017 was an incredible year. Cryptocurrencies came to be more mainstreaming accepted when the Chicago Board Options Exchange (Cboe) started offering Bitcoin futures and allowing investors to bet on the future direction of the cryptocurrency. Also, during the year many cryptocurrencies in circulation saw their prices escalate to new plateaus as investors throughout the globe poured money speculatively into these assets (Martin, 2017).

The year 2018 entered with an upward momentum following the approval of US tax policies in December 2017 (TCJA) and lower unemployment rates (3,7% for US in the month of September), with advanced economies showing higher growth rates, although some economies verified downside turns and there were fears regarding geopolitical forces between US and China. The "trade war" between these countries was fueled by higher tariffs announced by the President Donald Trump on steel (25% tax) and aluminum (10% tax) causing a global reaction amongst the leaders of other countries with worries about their own trade affairs with the US.

Capital markets in the US in 2018 observed much higher volatility in comparison to 2017. After a long period of continuous growth, the financial markets were affected by heavy selling in the month of February. Leaving severe cuts in the index's prices. But the market managed to pick up the pace and hit yet again record heights in the month of October.

For Cryptocurrencies this year started off with the burst of the "bubble" that had been escalating throughout the year of 2017. Much like the internet stock boom, investors that betted on the cryptocurrency future suffered an 80% decline. This is largely consistent with the perspective of emotions of investors being a dominating feature of the market. This shock is thought also to have had its origins from the accumulated hacks to cryptocurrencies before and in early 2018, new policy measures in Asian-Pacific countries in attempt to regulate crypto-trading and the lack of support from governments, institutions (e.g. The US Securities and Exchange Commission (SEC) refusal on approving Bitcoin ETF) and other important investors such as Warren Buffet (Carson, 2018).

In 2019 was characterized by stronger geopolitical tensions, specially between the US and China, which created uncertainty about global goods trading and investment decisions. In UK, Boris Johnson finally managing to pass the Brexit deal through the Parliament, raising concerns regarding trade between European Union members and Britain. The British Sterling Pound verified a strong decay in its value with a year low in September of 1,195$.

Additionally, frictions between US and the Middle East regarding Saudi Oil, which suffered an attack in September caused crude oil prices to spike, since its production halted in around 50%.

FED and monetary policy managed to alleviate the market sentiment towards an imminent recession due to inverted yield curves. The global financial markets responded with stable increases. With US equity markets hitting another year of record high, after US and China announced the phase 1 trade agreement. NASDAQ rose over the threshold of 9,000. As well as European equity, with the EuroStoxx600 managing a new record at the end of the year (NASDAQ, 2019).

For cryptocurrencies, the year of 2019 marked a decade since its origins. This year was one of recovery and of future promise regarding its technology and acceptance.

Bitcoin started on a year low of 4,000 USD and rose to 12,000 USD in July and 7,000 USD at the end of the year. On the other hand, the second most capitalized coin, Ethereum suffered an attack (51% attack) in January with estimated losses around 1.1 million USD. But besides these "hiccups" the market showed signs of progress, with important entrepreneurs such as Elon Musk standing behind the technology. And with the SEC announcing that Ethereum was not considered a security, and therefore it should not be regulated as such, it opened the market for more token offerings.

Additionally, in November, Chinese authorities discarded their plans of introducing bans to the mining practices in the country which was taken very positively by the cryptocurrency market.

Finally, the year of 2019 was an important step towards the mainstream use of blockchain technology not only in the cryptocurrency market but also by other businesses.

The year of 2020 was filled with hopeful expectations, but with the unfold of the Covid-19 pandemic these expectations were left ruined. The virus impacted heavily worldwide, with high human costs, stressing families to poverty levels and affecting global financial markets. From all countries the countries affected, China showed the greatest signs of recovery after containing to a certain extent the spreading of the virus (IMF global outlook report, 2020).

Financial markets saw a run of devastating fear and panic from the ongoing pandemic and widespread government lockdowns. The equity market "crashed" to unseen levels with the Dow Jones Industrial Average declining nearly 13%, and both S&P500 and NASDAQ indexes 12%.

Additionally, the continuing of the inverse US treasury yield curve indicated pessimistic economic outlook, with investors fleeing long-term riskier assets to short-term treasury securities. Although the treasury markets around the world were also affected with concerns surrounding the liquidity of the assets since debt levels increased at alarming pace, leading to panic selling. If not for the Federal Reserve intervention of Treasury purchase program that brought some confidence back to the fixed income market.

The fear indicator (VIX) after the fastest downturn of equity markets in history in March 2020, the VIX indicator rose to tremendous levels, indicating severe levels of uncertainty in the next 6 months.

And precious metals markets verified an all-time trading ratio record in the month of April.

Lastly, the cryptocurrency market observed yet again another incredible rise, with cryptocurrencies multiplying their price value many times over after the start of the pandemic. The fact that regulatory bodies, central banks and governments found tremendous difficulties in coping with such dramatic event, endorsed the unregulated cryptocurrency market which has been resilient throughout its existence.

Therefore, investors in a sense may have found refuge in the crypto market that during troubling times persisted (Earle, 2021).

Prospects of a vaccine in 2021 renew hopes of the recovery of the economy although still much uncertainty remained due to new varieties of the virus appearing (IMF global outlook report, 2021).

2.5.1 Origins and evolution of cryptocurrencies

The global financial crisis of 2008 and the subsequent liquidity challenges triggered traders, policymakers, and academics to take interest on a different form of money and investment asset, cryptocurrencies (Kyriazis, 2020).

These assets have been a centre of attention of many investors since the introduction of Bitcoin. Originally presented in a paper written by Satoshi Nakamoto (2008) and launched in 2009.

The digital currencies market has evolved drastically during the past decade with over 50 million active investors investing on Bitcoin and on many other cryptocurrencies that proliferated after. The market has increased in size considerably, growing from a few circulating cryptocurrencies to more than 4,000, and achieving a market capitalization on the 1st of January 2021 of 772 billion dollars (more than 4000% growth in just 4 years).

The main investors of cryptocurrencies are individuals, but that paradigm has gradually started to change, with more institutions backing these instruments, by applying cryptocurrencies to their balance sheet as a long-term investment, as a hedge against inflation and accepting them as payment methods [9]. For individuals' cryptocurrencies are also becoming more and more accepted as a method of exchange although still far from the global acceptance of traditional currencies (fiat currencies) which are backed by central banks and governments.

Cryptocurrencies are issued through a public sale denominated as ICOs (initial coin offering) and are often used as a means of funding to technology companies/start-ups, and are commonly traded on crypto exchanges, where investors can trade these assets with each other and against fiat currencies like the EUR and USD.

2.5.1 Comparison between Crypto and Fiat currencies

By definition, money is classified as "any asset that is generally accepted for payment for goods or services, or for debt settlement" (Revenda, 2005) and can be interpreted as "a social convention, with no intrinsic value which comes before its use,

[9] Financial institutions such as, Renaissance Technology entered Bitcoin futures market, while Goldman Sachs started to offer cryptocurrency products and Citigroup and other banks started to invest in these assets. There are companies that also accept Bitcoin as payment for goods and services, see https://99bitcoins.com/who-accepts-bitcoins-payment-companies-stores-take-bitcoins/. Companies, such as Bloomberg, Expedia, Gap, JC Penney, Microsoft, Subway, to name but a few, are on the list.

instead, its value is created by its constant exchange and use as money" (Weidmann, 2012).

In comparison with fiat currencies, such as the EUR and the USD, which comply with the three functions of money (medium of exchange, storage of value and a unit of account) as well as possess a universal claim on the economy, cryptocurrencies work as a good storage of value but fail to be accepted as a strong exchange medium to assume the same role in the current economy.

Having that said, todays trust in fiat currencies, Banks and Central Banks is not that favourable. Especially after the financial crisis of 2008, where doubts regarding the financial system framework were raised. The rise of cryptocurrencies, markedly bitcoin, has fuelled new and old debates about money, since modern economic theories fail to deal with monetary issues.

When it comes to digital currencies, the question remains in what makes market participants, trust in the coin itself, because as mentioned before, Bitcoin and other cryptocurrencies are not globally viewed as means to exchange for commodities, while in comparison fiat currencies are backed by some kind of social debt. Additionally, because some cryptocurrencies have an intrinsic characteristic of relatively fixed supply (limited amounts issued) and properties of tracking past transactions, they lack the dynamics of fiat currencies of spontaneous coin-creation and forward-looking claim.

It becomes apparent that cryptocurrencies have the necessity to reach a certain critical mass of users in order to reach similar recognition to that of the fiat currencies, which is usually driven by a positive feedback behaviour (Cheah 2015; Senner, 2018).

2.5.2 Blockchain

Cryptocurrencies and blockchain are often mentioned in the same sentence and are clearly linked to each other, but they should not be mistaken for one another. Blockchain is a type of distributed ledger technology that constitutes the backbone of the cryptocurrencies (Bratspies, 2018), although its range of applications are not limited to this particular market.

Blockchain can be and is applied in various sectors with a wide applications possibility. It is important to separate these applications and cryptocurrencies, which are but one specific application of this technology.

Blockchain in cryptocurrencies is capable of recording data across a multiple ledgers/data stores which are maintained and controlled by a network of computer servers (nodes) (Krause and Gradstein, 2017) employing mechanisms of encryption (cryptography) where more recent data can only be added to the already existing data, forming a continuous series of “transaction blocks”.

The technology can work on a permissionless or permission basis. The first (permissionless based), means a person can join and leave the network without any approval from a central entity, most cryptocurrencies in circulation are of this type. The second (permission based) require transaction validators, where nodes need to be pre-selected by a network administrator to be able to join the network.

There are two subcategories to the permissioned blockchains. One is open/public permissioned blockchains, which allow access by anyone, but only approved network participants can generate transactions and update the ledger (Jaychandran, 2017). And the other are closed permissioned blockchains, which transactions are reserved for the network administrators.

The main advantages of this technology are that it decentralises the authentication of transactions, simplifying the process that on norm needs the intervention of a third party (e.g. banks, brokers and others) (Witzig and Salomon, 2018). Additionally, it resolves the issue of double spending, which is the issue that one and the same payment instrument can be transferred more than once (Houben, 2017) through the application of consensus mechanisms, “Proof of work” (PoW) and “Proof of Stake” (PoS).

The PoW system works with the network participants to solve “cryptographic puzzles” to be able to add new information (blocks). This process is often called “mining” and requires a vast amount of computer resources and electricity.

The PoS, on the other hand, is a transaction validator system which requires proofs of ownership of the assets to validate transactions. This process is called “forging”, where the transaction validator gets paid a fee for his validation services.

Simply put, blockchain works in this sequence. First, new information’s to the blockchain database are added by one of the members (network nodes), who create a new block of data. This block is then passed on to everyone within the network in an encrypted form (through cryptography), so that the transaction details are not visible (Krause and Gradstein, 2017). Members of the network then validate the block accordingly to an algorithmic method (consensus mechanism -PoW or PoS), and once validated a new block is officially added to the chain (see Figure 3).

All blockchain networks possess a set of two keys. A private key for creating digital signatures of a transaction, and also a public key known by everyone in the network, which serves as an address on the blockchain and to verify signatures.

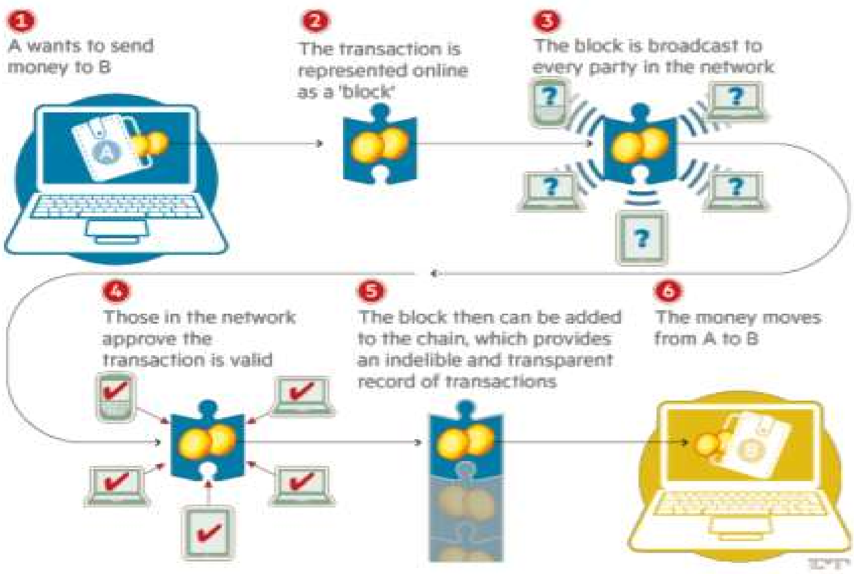


Figure 3: How blockchain works. Source: “Technology: Banks seeks the key to blockchain”, by J. Wild, M. Arnold and P. Stafford, 1 November 2015, Financial Times.

2.5.3 Cryptocurrency price drivers

Literature surrounding cryptocurrencies state its intrinsic characteristic of not having a specific underlying asset, meaning pricing method such as CAPM cannot be used to determine the value of the currency. (see Garcia et al., 2014; Godsiff, 2015; Yermack, 2015; Baek and Elbeck, 2015).

That said there are a number of factors that can influence its market prices, which can be divided into two main categories (Poyser, 2017). Internal factors, which include the supply and demand of the currencies and their technological characteristics. And external factors like asset attractiveness, legalization, and few macro-finance and political factors (interest rate, stock markets, gold prices; see Figure 4).

The first (internal factors), studies find that trading volume and exchange rate volatility are determinants of prices on short and long-term view (Li and Wang, 2017; Sovbetov, 2018). While in terms of technological characteristics, for example, the hash rate[10] and mining difficulty of Bitcoin is stated to have a significant impact on its price (Kristoufek, 2015; Li and Wang, 2017).

The second (external factors), can be separated into three subdivisions: (i) macro-financial, (ii) political and (iii) market sentiment. From the macro-financial perspective, Li and Wang (2017) shows that, since 2014, Bitcoin exchange rate is becoming more sensitive to macro-financial indicators, and Sovbetov (2018) found a short-term negative correlation between Bitcoin prices and the S&P500 index.

From the political side, the lack of centralization and regulatory supervision makes these assets more prone to speculation and news but also subject to country specific regulation problems, damaging the overall cryptocurrency acceptance as it is possible to see in the Figure 5 bellow. Regulation of cryptocurrency presents a challenge for policymakers, and many countries have since threatened to introduce bans on the use and trading of these assets, although few have yet implemented such regulations.

[10] Hash rate is the measuring unit of the processing power of the Bitcoin network. When the network reached a hash rate of 10 Th/s, it meant it could make 10 trillion calculations per second.

Announcements of such bans can provoke sudden drops in prices, like it occurred when China banned ICO's in September 2017, which is said to have led to a 500$ Bitcoin price decrease.

When it comes to the market sentiment, Mai et al. (2018) study concludes that more uplifting posts, on BitcoinTalk.org platform, are associated with higher future Bitcoin returns. Garcia and Schweitzer (2015) verify similar indicators of predictability by introducing Twitter tweets on a Bitcoin trading algorithm. Achieving the conclusion that social media sentiment can be used to predict future returns, although the relationship is complex.

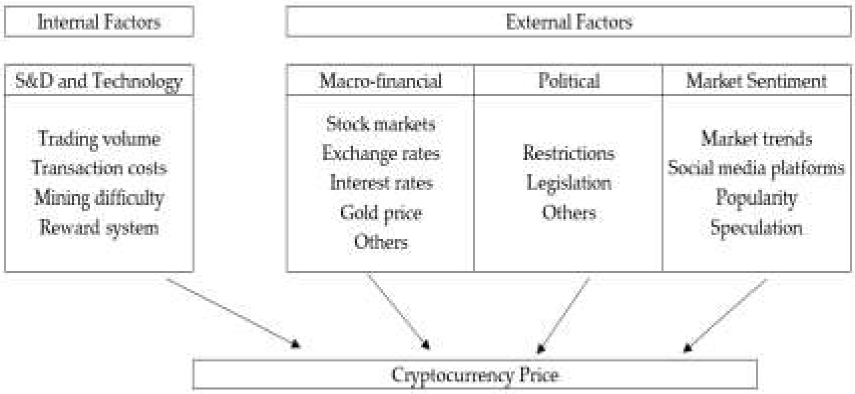


Figure 4: Cryptocurrency price drivers. Self-elaboration

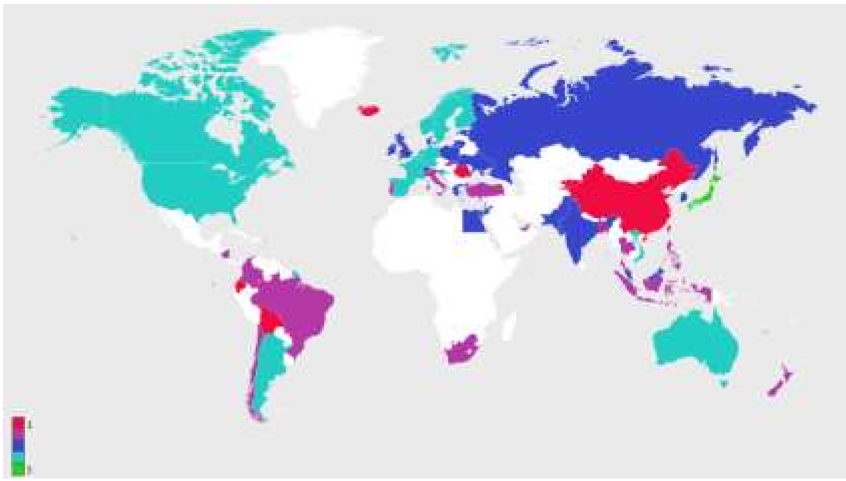


Figure 5: Recognition level of cryptocurrencies. Source: Synergy database.
Cryptocurrency regulation: 1 = Prohibited; 2 = Mostly Unfavourable; 3 = Mostly Favourable; 4 = Favourable; 5 = Legalized
Sixty-three percent of countries have favorable or mostly favorable regulation of cryptocurrencies out of 60 states studied as of July, 21st 2017. This is a very good sign for the industry. Still there is a lot of room for growth and diligent work with regulatory bodies to make cryptocurrencies widely acceptable.

2.5.4 Cryptocurrency overview and social dynamics

As mentioned previously, prices of digital cryptocurrencies fluctuate around the basic principle of supply and demand. But due to its lack of intrinsic value and a central cryptocurrency market regulation shifts in political standpoint, macro-financial indicators, on the technological properties in the cryptocurrencies and the overall market sentiment can lead to major volatility in the market.

Recently, and as mentioned previously, concerns especially from policy makers appeared. In the end of 2017, beginning of 2018, China sought to increase the supervision of foreign currency flows and transparency in cryptocurrency exchanges, incrementing the regulation prohibiting initial coin offerings (ICO's). South Korea also intervened by applying measures to ban anonymous trading on domestic exchanges, while foreigners and minors were completely prohibited of trading through cryptocurrency accounts.

Another major issue is related to the anonymity present in cryptocurrency transactions, which in conjunction with the rise of criminal activity portraying these assets and the rapid speed of cryptocurrency evolution makes major banking corporations wary of conducting business with crypto traders, undermining the reputation of the assets (Corbet et al., 2018). Also, and because of the connection of cryptocurrencies to issues such as terrorism, money laundering and tax-evasion, the social media platform Facebook introduced an advertising policy of not allowing advertisement concerning cryptocurrencies, binary options and ICO's. Supporting these worries, there were situations of cybernetic hacking in December 2017, where 70M$ worth of Bitcoin were stolen from NiceHash trading platform, and January of 2018 with a 530M$ disappearance from Coincheck.

Another issue raised, is the excessive amount of energy being spent by cryptocurrency activity. As mentioned previously, energy and computer power is a necessary requirement to comply with the mining processes. In the Bitcoin case, for example, the energy consumption is increasing at an alarming rate per transaction (764 KWh according to the Bitcoin sustainability report of February of 2018).

From the investors perspective the scenery is quite different. During the more recent timeframe, cryptocurrencies have observed another spike in prices from January 2020 to January of 2021, where for example the prices of Bitcoin rose more than four times (7200$ to 32700$). During this period, networking and macro-financial effects had an important weight in the prices' evolution (e.g. Online forums communities and the uncertainty caused by American presidential elections).

Some forums are the perfect illustration of the networking influence. Where users share opinions about the latest news and issues, such as sudden upward or downward movements. For example, Reddit platform, which covers several news and counts with more than 430M varied subscribers (sophisticated and unsophisticated).

Moreover, early adopters of these platforms are said to have a leveraged position and power capable of price manipulation (e.g. by declaring future increases in prices and technologic innovations in crypto) (Calderón, 2018). Investors in this market are then forced to distinguish from a sea of information, accurate and inaccurate information faster. Being sometimes easier and strategically rational to follow other investors and crypto market movements (Herding behaviour). Amongst the investors, there are some that believe to be more capable than the average ones in the market, having a chance of attaining gains form bubble circumstances by riding a storm of profits growth and exiting before the crash (Read, 2012), while others fall victim of their own euphoria (Shiller, 2015).

Therefore, the crucial lesson is that social judgment is intrinsic to the cryptocurrency market. And the lack of fundamental value and regulation, can create scenarios that highly resembles bubble formation events (e.g. tulip mania and the dot com bubble cases). Where investors act with over-optimistic assumptions of future gains, lack of caution and a panic of "not being a part" of the "wave" (Ofek and Richardson, 2001; Corbet et al., 2017; Calderón, 2018).

The likelihood of these events is also aggravated by the highly skewed market distribution, with Bitcoin holding roughly 70% of all market and Ethereum (second largest crypto coin) around 10% of the market (source: coinmarketcap.com), where a sharp collapse of Bitcoin can affect all the market. Situation that was verified in January 2018, where the overall confidence decreased substantially (Bitcoin prices fell by almost 50% in one month).

2.5.5 Empirical evidence on Cryptocurrency and herding

The subject of the cryptocurrency markets is still relatively new, and empirically speaking, the application of behavioural finance models has helped not only to better understand these instruments but also to shed some light on how this market behaves.

Behavioural Finance suggests that the volatility and excess trading in the cryptocurrency markets can be explained due to irrational behaviour of investors, and the fact that the market is characterised by high volatility endorses individual's sentiment of missing out on an opportunity to profit, leading to herding behaviour (Cheah, 2015). Herd behaviour as discussed in previous chapters is the act of individuals to group and move in conformity of another (herder directs the group). However, in speculative markets, such as cryptocurrency markets, there is no one to direct, and instead they follow the information they receive pertaining the asset itself or herd towards an optimistic sentiment or news creating situations of market fragility or even crashes (Welch, 2000; Liu, 2018; Senarathne, 2020).

When revising the existing literature that links herding to the cryptocurrency market, herding appears to exist in the cryptocurrency market in most of the cases. Researchers found significant results of its presence through the use of the rolling window regression methods (Amirat, 2009 and Bouri et al., 2019), and through the cross-sectional absolute deviation models (Ajaz and Kumar , 2018; Kallinterakis and Wang 2019; Tomàs, 2019; Ballis and Drakos, 2020; Kyriasis, 2020; Jalal et al., 2020; Senarathne and Jianguo, 2020 and Yousef, 2020). All of them used a different sample for testing, ranging from the year 2013 to 2019, and different chosen cryptocurrencies and market benchmarks.

Where the study's results differ, is in the intensity of herding across different market conditions. There are results pointing to herding behaviour during a downward market period, suggesting the inefficiencies of the cryptocurrencies (Tomàs, 2019). While contrary, Ballis and Drakos (2020) and Kyriasis (2020) found herding to be more evident in bullish moments, since market dispersion was verified to be faster in upward price movements. Also, Kallinterakis and Wang (2019) results indicate using dummy variables on both volume and volatility that herding is considerably stronger during bullish trends, with small cap cryptocurrencies having a strong ponderation on reinforcing the intensity of herding.

Ajaz and Kumar (2018) and Jalal et al. (2020) verified herding in both situations (bullish and bearish markets) indicating that investors follow the masses and buy/sell cryptocurrencies massively, exhibiting overreaction patterns. While Bouri et al. 2019 provide evidence of herding in subperiods of their analysis, indicating that herding intensity is not stable across different time periods.

Other studies managed also to connect herding behaviour in the cryptocurrency market with external indicators. Yousef (2020) found suggesting results that increases in market volatility, the S&P500 index and the dollar index promote more intensity of herding behaviours, while the increase of trading volume, gold prices and the Economic Policy Index (EPU) were found to be inversely related to herding in the Cryptocurrency market.

Amirat (2019), on the other hand, found an inverse relationship between herding behaviour and the Bloomberg consumer comfort index, meaning that when traders are less comfortable, they prefer to ignore their expectations and follow the "herd" to the average market performance.

In contrast, Senarathne and Jianguo (2020) explored whether herding behaviour in the cryptocurrency markets was tendentially spurious or intentional, and the results of the study pointed to a strong tendency to herd on non-fundamental information (e.g. market sentiment), meaning crypto returns cannot be predicted from fundamental economic information, like macroeconomic announcements. Additionally, since low correlation between the other variables/assets (no relationship between CSAD and CCi30, US equity risk premium, and US/Euro exchange rate return) was verified, this could mean that cryptocurrencies can be used as a means of portfolio diversification.

From all the studies gathered is possible to assume that herding behaviour in the cryptocurrency market exists to a significant degree, but there are uncertainties regarding its intensity during market upward and downward movements as well as to whether this behaviour in the market is a product of the sentiment of investors or macroeconomic conditions.

This disparity of results is likely to be due to the different sample used for the analysis, since herding behaviour is mentioned to last differently (from a few months to just a days) as pointed out by Bouri et al. (2019), depending on market conditions.

2.6 Hypothesis

H_1: Herding behaviour is significantly present in the Cryptocurrency Market.

From the reviewed literature, it is possible to infer that the cryptocurrency market possesses a highly speculative nature derived from the non-regulation risks and technological complications surrounding these assets, like hacking and cybernetic attacks. Their prices were also discussed to be susceptible to news, trends and networking effects, provoking sentiment on investors as to not miss out on an opportunity (Cheah, 2015), but also to panics and mass sell outs as verified in early 2018, which are consistent with the possibility of herding behaviour. These findings can also be related to high individual investor trading in the market since they are thought to be more prone to informational and social interaction biases.

Additionally, both cryptocurrencies and financial markets saw a fair share of shaking events from 2017 to 2021. These 4 years were ruled by severe political and economic uncertainty which in the case of the cryptocurrency market may also have facilitated herding behaviour in the market. Because when investors are before unprecedented events, they are more likely to follow the crowd in the expectation of better results.

Lastly and most importantly, the empirical studies reviewed point to the existence of herding in the cryptocurrency market using the CSSD and CSAD methods for testing, such as the ones of Ajaz and Kumar , 2018; Kallinterakis and Wang 2019; Tomàs, 2019; Ballis and Drakos, 2020; Kyriasis, 2020; Jalal et al., 2020; Senarathne and Jianguo, 2020 and Yousef, 2020, which reinforces the positive validation of hypothesis 1.

H_2: Herding intensity changes during asymmetrical market returns periods.

The testing of this second hypothesis aims to give additional robustness to the existing literature, since there are mixed findings on most of the markets. Although generally most conclusions show heavier herding signals during downward market periods in comparison to upward ones. These results indicate that investors sentiment of fear and panic is often stronger than those of over enthusiasm (Lindhe (2012).

From the cryptocurrency perspective, the conclusion is also mixed. There have been periods that appear to have had high levels of euphoria (2017 and 2020) and other of panic (2018), which is consistent with Bouri et al. (2019) claims of herding depend on market conditions. That being said, it's expected that herding will be more or less intense during instances of bullish and bearish market movements, similarly also to the results of Ajaz and Kumar (2018) and Jalal et al. (2020).

This approach can play an important role on portfolio and risk management judgments of investors by permitting an anticipation shifts in market trends and also better portfolio diversification.

Chapter 3
Data and Methodology

3.1 Data

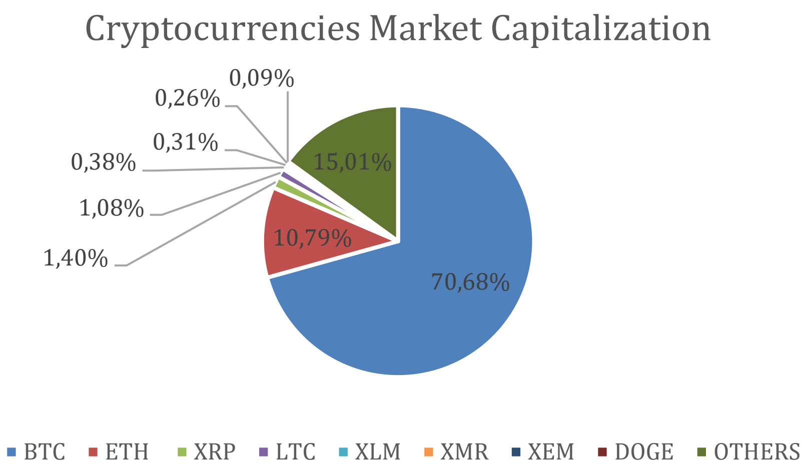
This thesis is based on secondary data, which observations include eight major capitalized Cryptocurrencies Bitcoin (BTC; 70,68%), Ethereum (ETH; 10,79%), Stellar (XLM; 0,38%), Dodge (DOGE; 0,09%), XRP (XRP; 1,40%), Litecoin (LTC; 1,08%), Monero (XMR; 0,31%) and NEM (XEM; 0,26%), a market representative index (CCi30).

The eight cryptocurrencies were chosen because of their strong market capitalization (see graph 1) and also due to their antiquity (originated before 2017) in order to have consistent and relevant data with a good representation of the overall market.

Unlike traditional assets, cryptocurrencies trade all days of the week, and for empirical testing was gathered closing daily prices in USD (see graphs 2 to 10 in appendix) extracted from https://coinmarket.com and https://cci30.com, for all the respective variables during the period of 01/01/2017 to 01/01/2021 (1461 days).

The https://coinmarket.com is a website that regularly collects data on cryptocurrency from multiple exchanges and is commonly used in empirical research (see Bouri, 2018; Calderón, 2018; Kumar, 2018; Senarathne and Jianguo, 2019).

Also, it is important to mention that the data that will be under study will encompass outliers, since they are relevant to verify herding behaviour under irregular market dynamics and account for the asymmetric reaction during bullish and bearish markets (see Chiang and Zheng 2010)



Graph 1: Cryptocurrencies Market Cap. 1st of Jan. 2021. Source: coinmarketcap.com

3.1.1 Bitcoin (BTC)

Bitcoin is an online communication protocol that facilitates the use of a digital currency as a form of electronic payment (Böhme et al., 2015). It is built on a PoW consensus mechanism and a permissionless blockchain (see figure 6), that is distributed across a network of peer computers.

Therefore, for safekeeping of each transaction of Bitcoins on the blockchain, built-in incentives, such as Bitcoins or fees are provided to individuals denominated as "Miners," (Brito, 2013) who keep and maintain the security level of Bitcoins by verifying each transaction. Consequently, the currency is obtainable through two main sources, by "mining" process or by exchanging it with conventional currencies on specialized websites (e.g. Coinbase, Kraken, Anycoin Direct and others).

Another important point of this currency is that it lacks a centralized authority capable of adjusting the currency quantity in circulation like a Central Bank, making the process of issuing and verification of transaction more difficult. So, for the time being, Bitcoin issues new currency to private entities ("Miners") at a controlled pace as a compensation for their services.

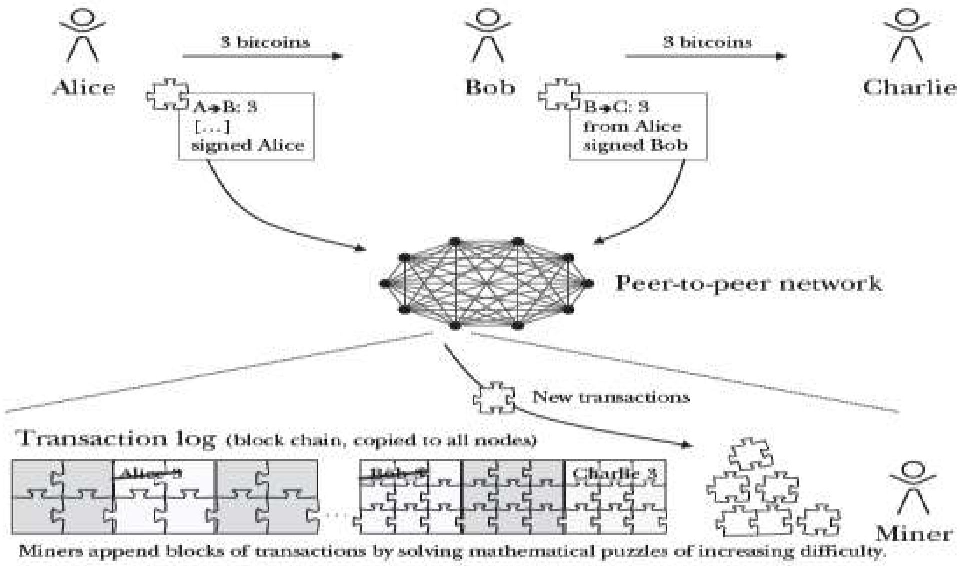


Figure 6: Bitcoin's transaction flow and validation. Source: Böhme R. et al. 2015

3.1.2 Ethereum (ETH)

Ethereum was founded in 2014 by Vitalik Buterin, Gavin Wood and Jeffrey Wilcke, with an initial emission of 60 million tokens. The cryptocurrency as a whole can be viewed as a transaction machine, which allows smart contracts to run on a decentralised blockchain (see Figure 7), where are only executed if certain conditions are met (Wood, 2014; Buterin, 2016). For example, in a traditional finance deal each party uses a paper or a digital contract subject to individual modifications, on the other hand smart contracts are written code in the blockchain, and once the terms of the contract are met the deal is executed.

Technically speaking, the Ethereum platform is not a cryptocurrency, however works all the same on a permissionless blockchain, which requires a form of incentivised validation of the network, that occurs through "Ether". "Ether" is the currency of the Ethereum network, which allows smart contracts to be built and functions as a mean of exchange.

The blockchain design is universal and programmable, meaning anyone can use to release their own decentralised applications (Dapps) and create smart contracts that enforce their clauses (Tikhomirov, 2018). Similarly to Bitcoin, miners are used to verify each transaction in return of a fee, but unlike Bitcoin, Ethereum does not have a coin supply limit.

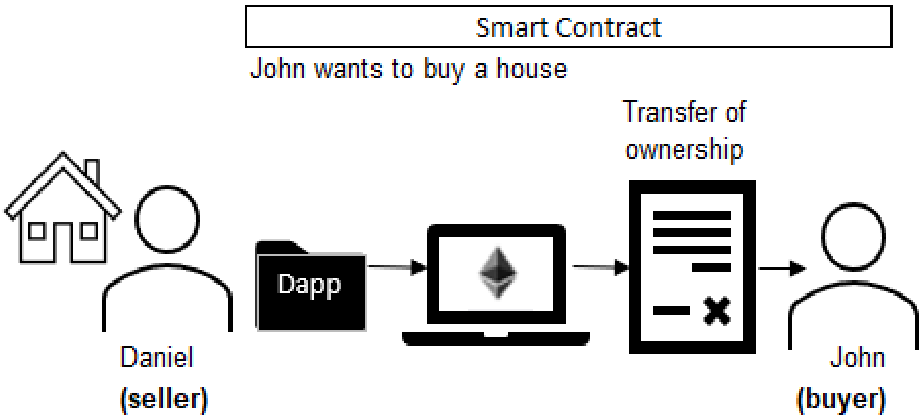


Figure 7: Ethereum Smart contract. Source: Buterin, V. 2016.

3.1.3 Stellar (XLM)

Stellar is a blockchain-based global payment network designed to promote innovation and competition in international payments. It started in September 2015 and is known for allowing transfers and for processing multiple currencies anywhere in the world in seconds.

The Stellar blockchain technology has two distinguishing characteristics. First, it supports efficient markets across currencies and issuers by providing a built-in orderbook for trade between any pair of coins where users can issue a payment path that will atomically trade across several currency pairs, while guaranteeing the end-to-end limit price. Second it introduces a main innovation that is the secure transaction mechanism through the use of a new complex agreement protocol called SCP (Stellar Consensus Protocol). With this protocol each issuer designates a specific validator server to enforce transactions finality, and as long as no one compromises the issuers validator, the issuer will know exactly what transactions occurred and avoids the loss risk from blockchain reorganization (Lokhava et al., 2019).

Stellar is cryptocurrency Lumen (XLM) can be used for payments on the network while allowing an anti-spam role, since each transaction requires a small transaction fee, which is paid for in the cryptocurrency. The currency itself complies with three objectives: (i) Open-membership (anyone can issue digital currency tokens that can be exchanged on the network), (ii) issuer-enforced finality (a coin issuer can stop transactions in the same currency from being reversed or undone) and (iii) cross-issuer atomicity (users can atomically exchange and trade from multiple digital coins issuers).

3.1.4 Litecoin (LTC)

Litecoin was launched in October 2011 as a rival of Bitcoin. The same way Bitcoin is perceived as the "digital gold", Litecoin's founder Charlie Lee intended Litecoin to be the "digital silver".

Therefore, it presents the same decentralised characteristics, but with the enhanced purpose to process smaller value transactions faster and facilitate the mining process, which contrary to Bitcoin can be done by a normal desktop instead of a supercomputer.

Litecoin has 84 million coins of supply, four times larger than Bitcoin, and a transaction processing time of 2,5 minutes, four times less than that of Bitcoin (Bhosale and Mavale, 2018). This faster processing, although a great feature to resist double spending attacks, it has its drawbacks, since it also means larger blockchain size and orphaned blocks (Gibbs and Yordchim, 2014).

3.1.5 Dodge (DOGE)

Dodge coin was invented by Billy Markus and Jack Palmer in 2013 as a joke, now is described as an established "member" of the cryptocurrency community, occupying a place in the top capitalized currencies. The structure of DOGE is based on existing cryptocurrency like Luckycoin, which featured a randomized reward for the act of mining on the blockchain, although today runs on a static fee.

Contrary to Bitcoin this coin does not have a supply limit, and therefore uses a built-in inflationary momentum system. Additionally, the transaction process is of 1 minute, faster than the 2,5 minutes of Litecoin.

The coin found a niche to belong to, as an online system for tips, where social media platforms grant DOGE currency to others in return of notable content, and has been seen present on fundraising initiatives (e.g. world water day) (Chohan, 2021).

3.1.6 Monero (XMR)

Monero's objective is to address issues of traceability and anonymity present in other cryptocurrencies (e.g. Bitcoin). As a privacy-centric cryptocurrency, it is concerned with making payments untraceable.

Technically, the coin is based on the CryptoNote PoW protocol and achieves greater anonymity through the use of three methods: stealth addresses, that are one-time use keys generated from a recipient address to prevent the identification of transactions (unlikability); Ring Signatures, which mix real expenditure with other decoy outputs; and lastly, confidential transactions, which hide the value of non-mining transactions, preventing tracing through amount (Hinteregger and Haslhofer, 2019), (see Figure 8).

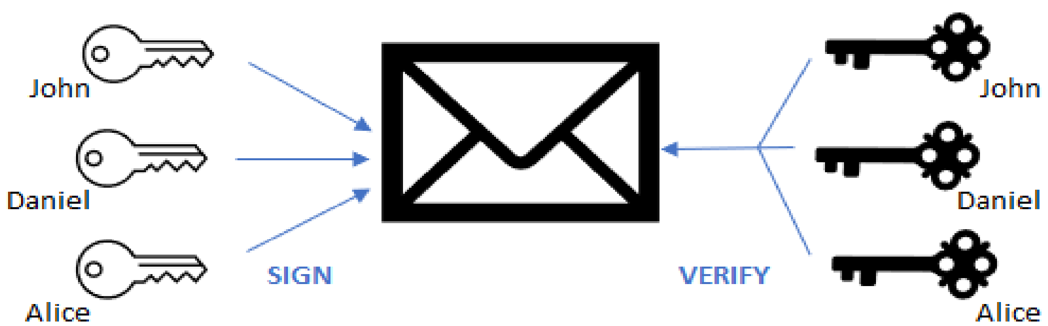


Figure 8: Ring signatures exemplification.

3.1.7 NEM (XEM)

NEM platform, short for New Economy Movement, was introduced in March 2015, and is a peer-to-peer platform that provides services like online payment and messaging system (Quasim, 2020).

It has a permissioned private blockchain with an innovative consensus system called POI (Proof-of-Concept). NEM, contrary to most cryptocurrencies, uses "harvesters" to determine a participant, where more important accounts will have a bigger probability of being chosen to harvest a block (to become eligible to harvest a participant must own at least 10,000 XEM).

The platform also provides an alternative for API developers looking to develop blockchain apps, and overall, its attention is focused on trading, banking and charity.

3.1.8 Ripple XRP (XRP)

XRP, formerly known as OpenCoin Ripple was launched in 2012 by a company called OpenCoin. It was created for the payment and exchange network called RippleNet. Its main objective is to connect banks, payment providers and digital assets exchanges, promoting faster and cost-efficient transactions across the globe (Quasim, 2020).

XRP offers another and more centralized medium of security mechanism supported by a customized algorithm based on the Byzantine Consensus Protocol known as RPCA (Ripple Protocol Consensus Algorithm).

This cryptocurrency therefore operates in a different way than the rest of cryptocurrencies, raising questions about its true decentralised nature.

The table 3 bellow summarizes the understanding of the eight selected cryptocurrencies. Making a clear distinction between each of them is not easy because of the complicated technological factors that compose each of them and the scarcity of information available. Additionally, since cryptocurrencies have "moving characteristics" (e.g. can be a medium of exchange today, and tomorrow they are no longer), continuous updates need to be taken into consideration.

Cryptocurrency	Characteristic	Technology	CoinSupply	Security
BTC	Digital Gold	Blockchain	Limited – 21M	Miners
ETH	Smart Contract	Blockchain	Unlimited	Miners
XLM	SCP	Blockchain	Unlimited	SCP
LTC	Digital Silver	Blockchain	Limited – 84M	Miners
DOGE	Tipping	Blockchain	Unlimited	Miners
XMR	Anonymity	Blockchain	Unlimited	CryptoNote
XEM	POI	Blockchain	Unlimited	Harvesters
XRP	RPCA	Blockchain	Limited – 100M	OpenCoin

Table 3: Comparison between cryptocurrencies. Self-elaboration.

3.1.9 CCi30 Index

The Cryptocurrency market representative index, CCi30, serves as the benchmark for the empirical study. The index covers the top 30 capitalized coins, capturing 90% of the market, with a confidence level of 99% and a margin of error of the index value of just 1,11%, while considering diversification advantages and taking into account the "lion's share" of Bitcoin (BTC) and Ethereum (ETH) capitalization, therefore the assets are weighted proportionally to the square root of their market capitalizations. This methodology promotes a more slowly decaying weighting as opposed to an equalitarian weighting scheme, which would give too much ponderation to the small and not very liquid cryptocurrencies.

3.2 Variables

For all the chosen cryptocurrencies and CCi30 index during the period of 01/01/2017 to 01/01/2021 (1461 days), was performed calculations on the daily closing prices to achieve the daily returns for all variables (1460 days), given by the following formula:

Daily Return (Rd) = $\frac{CP_t - CP_{t-1}}{CP_{t-1}} - 1$, where CP_t is the closing price day t and CP_{t-1} is the closing price the day before t.

The calculation of simple returns was chosen instead of logarithmic returns because, even though log returns can be useful for time series modelling due to the practical statistical properties, they carry a different weight when the distribution is skewed like the cryptocurrency market. Additionally, the relationship between risk and return calculated using log returns will persistently be different from those of simple returns (Hudson, 2015), and it does not provide a direct measure of the change in prices over a period of time necessary for this study.

3.3 Methodology

3.3.1 Cross sectional standard deviation (CSSD)

There are a few quantitative models that are used to measure herding behaviour in Financial markets. These quantitative approaches offer a palpable explanation behind the volatility in high speculative markets, which modern finance theories based on rationality are unable to explain (Javaira, 2015). One of the models is the Christie and Huang's (1995) cross-sectional standard deviation (CSSD), which equation of measure of return dispersion is the following:

$$CSSD_t = S_t = \sqrt{\frac{\sum_{i=1}^{N}(R_{i,t} - R_{m,t})^2}{N-1}}$$

Where St is the return dispersion at time t, N is the number of cryptocurrencies, $R_{i,t}$ is the return of the asset i at time t, and $R_{m,t}$ is the cross-sectional average of the N assets in the portfolio at time t.

The rationale behind the Cross-Sectional Standard Deviation model is that the asset pricing models (CAPM) assume that return's dispersion increases in conjunction with the absolute value of market return, but the assumptions of rational valuations models do not hold in every situation after being found evidence of herd behaviour.

In that sense, if investors trust market expectations and follow them their returns will not deviate from the average market returns, and the variance or dispersion level, used to measure herding behaviour presence between individuals return and the market, should assume the value of zero. Oppositely, when investors return differ from the market return, dispersion increases around the mean, indicating that herding is less present (Tan, 2008; Patterson, 2004).

Additionally, and considering these assumptions Christie and Huang (1995) estimate a model to determine the existence of asymmetric behaviour in extreme bullish and bearish market situations, described by the following equation:

$$CSSD_t = \alpha + \beta^L D_t^L + \beta^U D_t^U + \varepsilon^t$$

Where D_t^L is equal to 1, if the market return on day t lies in the extreme lower tail of the return distribution, or zero otherwise. D_t^U is 1 if the market return on day t is located in the extreme upper tail of the return distribution or 0 otherwise. If the estimates for the coefficients β^L and β^U are negative, and statistically significant, we can assume the presence of herd behaviour. On the other hand, if the estimates for β^L and β^U are positive, and statistically significant, the dispersion of stock returns tends to increase with extreme market movements, and this is consistent with asset valuation models, and inconsistent with the existence of herding towards market consensus.

One important defect of Cross-Sectional Standard Deviation (CSSD) approach is the assumption that the relation between the dispersion in securities returns and the market portfolio return is linear, meaning that changes in values of securities returns dispersion has an identical change at in the market portfolio return. Economu et al. (2010) arguments that the measure is therefore not robust enough in the presence of outliers, having a direct impact on the results.

3.1.2 Cross sectional absolute deviation (CSAD)

To tackle the issues of robustness against outliers, Chang et al. (2000) proposed another alternative, known as cross-sectional absolute deviation (CSAD) model. The main idea of this approach is to assume a non-linear regression, which aims to determine the relationship of asset return dispersion, measured by the absolute deviation of returns, and the return of the market.

If herding behaviour becomes apparent among investors, the relationship between dispersion and market return in extreme market circumstances, is expected an increase at a less than proportional rate, or even a decrease of the standard deviation of returns.

The $CSAD_t$model is expressed by the following equations:

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

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

Where $\left|R_{m,t}\right|$ represents the absolute value of the market return, and a non-linear term ${R^2}_{m,t}$ which assumes a correlation between returns increases at a rate that is not proportional to the benchmark variable.

By conciliating with the Capital Asset Pricing Model (CAPM) as a starting point to illustrate the relationship between market return and the dispersion of returns Chang et al. (2000) presents the following regressions on upward and downward movements:

$$CSAD_t^{UP} = \alpha + \gamma_1^{UP}\left|R_{m,t}^{UP}\right| + \gamma_2^{UP}(R_{m,t}^{UP})^2 + \varepsilon^t$$

$$CSAD_t^{DOWN} = \alpha + \gamma_1^{DOWN}\left|R_{m,t}^{DOWN}\right| + \gamma_2^{DOWN}(R_{m,t}^{DOWN})^2 + \varepsilon^t$$

Where $CSAD_t$ is the average absolute value of the deviation of each asset relative to the return of the market portfolio ($R_{m,t}$) consisting of N assets in the period t. $|R_{m,t}^{UP}|$ ($\left|R_{m,t}^{DOWN}\right|$) is the absolute value of an equally weighted realized return of all available securities on day t when the market is up (down). If no herding activity exists in the market and the rational asset pricing models prevail, the regression should demonstrate linearity (i.e. y_2 = 0). While a non-linearity is captured by the inclusion of a nonlinear term. A statistically significant negative coefficient (y_2 < 0) can be understood as deviations from linear asset pricing model and henceforth reveals the presence of herding behaviour.

Another variation to the latest model presented was suggested by Chiang and Zheng (2010) represented by the following equation:

$$CSAD_t = \gamma_0 + \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 R^2_{m,t} + \varepsilon_t$$

This model is used to test the robustness of the CSAD model of Chang et al. (2000) and if the results present a coefficient γ_3 is negative and statistically significant, then herding behaviour is said to be present.

3.1.3 CSAD for measuring herding intensity

In order to measure if herding is more common on periods of high returns than in declining returns, a variant of CASD model is proposed by Chiang and Zheng. It includes a dummy variable component D^{mt}, which assumes a value of 0 if the $R_{m,t}$ > 0 for bullish trends, and $D^{mt} = 1$ under bearish moments ($R_{m,t}$ < 0). The equation is expressed in the subsequent form:

$$CSAD = y_0 + y_1 (1 - D^{\mathrm{mt}})|R_{m,t}| * + y_2 D^{\mathrm{mt}}|R_{m,t}| + y_3(1 - D^{\mathrm{mt}})R^2{}_{m,t} + y_4 D^{\mathrm{mt}} R^2{}_{m,t} + \varepsilon_t$$

This model can be useful in detecting if herding is clearer during a crisis and extremely asymmetric market situations. If y_3 is significantly negative then herding exists during bullish market moments, and if y_4 is significantly negative then herding exists during bearish market moments. However, if the results are positive it may indicate anti-herding behaviour.

3.1.4 Models' limitations and future possibilities

All the models presented are used to estimate herding behaviour in markets, but capturing this particularity based on past information is not always straight forward. As discussed in previous sections the human mind is extremely complex and everchanging, making these models less able to capture information. New models are being developed in order to predict this behaviour rather than capture it, such as models derived from HIX index (herding behaviour index), which can be useful for investors to make better informed decisions (see Guillaume and Linders, 2015).

3.1.5 Structure of the empirical tests

The empirical tests of this study will be divided into two sections: (i) the verification of the presence of herding behaviour in the market and (ii) the measurement of the intensity of the same behaviour under market asymmetries.

For the first part, the analysis of the presence of Herding behaviour. The CSAD model Chang et. al (2000) variation of Chiang and Zheng (2010) for more robust conclusions was used.

Having this in mind, for the first hypothesis (test the presence of herding in the Cryptocurrency markets), it was first applied the the following formulas (i to iii):

(i) $CSAD_t = \frac{1}{N}\sum_{i=!}^{N}\left|R_{i,t} - R_{m,t}\right|$, $R_{i,t}$ are the daily returns of the cryptocurrencies, and $R_{m,t}$ represents the average return of the market at time t.

(ii) $CSAD_t = \alpha + \gamma_1\left|R_{m,t}\right| + \gamma_2 R_{m,t}^2 + \varepsilon^t$, where $\left|R_{m,t}\right|$ represents the absolute value of the market return, and a non-linear term $R^2{}_{m,t}$

(iii) $CSAD = \alpha + y_1 R_{m,t} + y_2\left|R_{m,t}\right| + y_3 R^2{}_{m,t} + \varepsilon_t$, where $R_{m,t}$ represents the average return of the market at time t, $\left|R_{m,t}\right|$ represents the absolute value of the market return, and a non-linear term $R^2{}_{m,t}$

For the second hypothesis of this research, the CSSD model was discarded, since several studies point this model as less reliable in the presence of outliers (Economu, 2011). Consequently, to understand herding behaviour intensity during asymmetric periods, was also applied the model variant of Chang et al. (2000) for upward and downward trends in the market, as well as the Chiang and Zheng (2010) model which introduces dummy variable to capture movements. Verifying if herding is more visible during each moment.

The equations are given by the following formulas (iv to vi):

(iv) $CSAD_t^{UP} = \alpha + \gamma_1^{UP}\left|R_{m,t}^{UP}\right| + \gamma_2^{UP}(R_{m,t}^{UP})^2 + \varepsilon^t$, where $R_{m,t}^{UP}$ is the absolute value of an equally weighted realized return of all available securities on day t when the market is up, and y_2^{UP} detects herding in upward market movements.

(v) $CSAD_t^{DOWN} = \alpha + \gamma_1^{DOWN}\left|R_{m,t}^{DOWN}\right| + \gamma_2^{DOWN}(R_{m,t}^{DOWN})^2 + \varepsilon^t$, where $R_{m,t}^{DOWN}$ is the absolute value of an equally weighted realized return of all available securities on day t when the market is down, and y_2^{DOWN} detects herding in downward market movements.

(vi) $CSAD = y_0 + y_1(1 - D^{\mathrm{mt}})\left|R_{m,t}\right| * + y_2 D^{\mathrm{mt}}\left|R_{m,t}\right| + y_3(1 - D^{\mathrm{mt}})R^2{}_{m,t} + y_4 D^{\mathrm{mt}} R^2{}_{m,t} + \varepsilon_t$, where D^{mt} is the defined dummy variable used to detect upward and downward trends.

3.4 Testing software

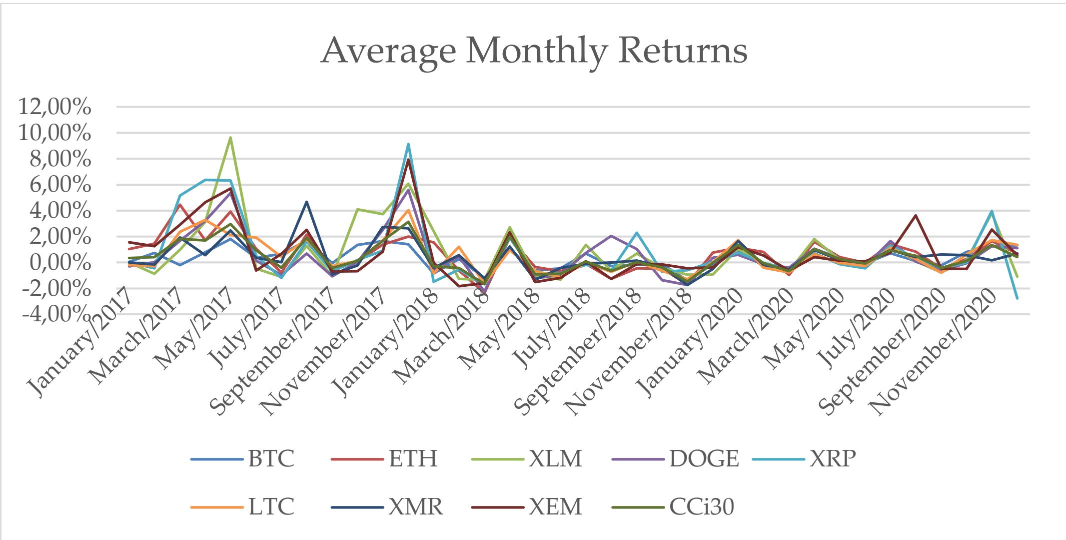
For the examination of the acquired data the data analysis tool of excel was used to reproduce the results displayed in the next chapter.

Although other statistical software could be used for the analysis of the data, such as Stata, SPSS, Gretl and others, the sample of study is not sufficiently big to justify that change. Moreover, Excel, even though not a specifically statistical tool is quite powerful and capable of attaining the same results (Mélard, 2014.; Hossein, 2020).

Chapter 4
Discussion

4.1 Data characteristics

When observing the evolution of average monthly returns from January 2017 to January 2021, of the eight chosen cryptocurrencies and the market index (see graph 3), its possible to see two major spikes, one around May 2017 and another around the end of 2017. As mentioned in the previous chapters, these periods were of tremendous volatility for cryptocurrencies, including a burst of the cryptocurrency bubble around the end of 2017, beginning of 2018.



Graph 2: Average monthly returns from January 2017 to December 2020

Amongst all the average monthly returns extracted from the data, the cryptocurrency XLM and XRP show the greatest volatility with a maximum average month value of 9,64% and 9,14% respectively and a minimum of -1,34% and -2,78%. Contrary to what one might expect, Bitcoin, presents the most stable average monthly returns of all the data, with maximum and minimum values ranging from 1,81% to (1,38%).

	BTC	ETH	XLM	DOGE	XRP	LTC	XMR	XEM	CCi30
Maximum	1,81%	4,46%	9,64%	5,60%	9,14%	4,03%	4,67%	7,93%	3,13%
Minimum	-1,38%	-2,35%	-1,34%	-2,27%	-2,78%	-1,65%	-1,75%	-1,83%	-1,66%

Table 4: Maximum and Minimum average monthly returns from January 2017 to December 2020

By employing the average monthly returns, one might not think that these instruments as extremely volatile, much less with bubble burst events. But when looking at the maximum and minimum values of the daily returns (see table 5 bellow, and table 13 in appendix) and daily prices (see table 6) it is possible so see why these assets are called speculative.

	Min 2017	Max 2017	Min 2018	Max 2018	Min 2019	Max 2019	Min 2020	Max 2020
Bitcoin	-18,74%	25,25%	-16,85%	13,22%	-14,09%	17,36%	-37,17%	18,19%
Ethereum	-27,06%	33,66%	-18,69%	18,07%	-16,74%	15,60%	-42,35%	18,94%
Stellar	-30,67%	106,09%	-26,38%	58,68%	-12,87%	30,38%	-33,64%	49,69%
Dodge	-38,92%	61,16%	-30,79%	49,53%	-10,91%	19,76%	-29,62%	53,72%
XRP	-46,01%	179,40%	-29,76%	37,96%	-12,56%	25,68%	-42,33%	39,68%
Litecoin	-32,64%	66,59%	-19,09%	33,73%	-16,50%	30,82%	-36,17%	21,05%
Monero	-25,41%	53,77%	-22,80%	19,27%	-17,30%	15,16%	-38,99%	15,13%
NEM	-30,33%	170,59%	-25,90%	54,31%	-17,24%	25,26%	-26,48%	33,95%
CCi30	-23,23%	19,52%	-22,92%	15,36%	-15,13%	15,78%	-38,40%	18,57%

Table 5: Maximum and minimum daily returns per year.

One of the most iconic characteristics of cryptocurrencies is the large deviations from the mean, as it is possible to confirm in the table above, that cryptocurrencies vary tremendously during the year, with returns reaching as high as 179,40% of return in a day and as low as -46,01%. This sequence of escalations and downturn of returns on a daily basis suggests that there are behavioural forces driving cryptocurrency prices.

	Min 2017	Max 2017	Min 2018	Max 2018	Min 2019	Max 2019	Min 2020	Max 2020
Bitcoin	777,76	19 497,40	3 236,76	17 527,00	3 399,47	13 016,23	4 970,79	29 001,72
Ethereum	8,17	826,82	84,31	1 396,42	104,54	336,75	110,61	751,62
Stellar	0,0017	0,3608	0,0954	0,8962	0,0434	0,1415	0,0334	0,2064
Dodge	0,0002	0,0094	0,0021	0,0171	0,0018	0,0039	0,0015	0,0048
XRP	0,0054	2,3000	0,2637	3,3800	0,1837	0,4748	0,1396	0,6921
Litecoin	3,71	358,34	23,46	296,45	30,33	141,90	30,93	130,05
Monero	10,64	469,20	38,85	459,33	42,80	117,42	33,01	167,94
NEM	0,0033	1,0600	0,0580	1,8400	0,0310	0,0994	0,0319	0,3031
CCi30	276,35	15 375,10	1 734,35	20 796,60	1 877,22	5 374,46	1 938,49	7 605,17

Table 6: Maximum and Minimum daily prices in USD each year.

In corroboration, we can verify in the table above that prices of cryptocurrencies during the year can be erratic. All the cryptocurrencies and the market index show a disparity of several times between the maximum price and minimum prices (see also graphs 3 to 20 in appendix) across the year of 2017 to 2020. Large and fast upswings and downswings in these assets prices also supports the theory of investors in this market assume a speculative and optimistic attitude towards risk, expecting to draw out financial gains from short-term price climbs.

4.2 Descriptive statistics

The descriptive statistics of the selected the group of eight cryptocurrencies, the market benchmark (CCi30), as well as the Cross-Sectional Absolute Deviations (CSAD) of the daily returns of the cryptocurrency market are displayed mathematically in the table 7 bellow:

Variables	**Mean**	**Median**	**Min.**	**Max.**	**Std. Dev.**	**Skewness**	**Kurtosis**
BTC	0,00320	0,00248	-0,37169	0,25247	0,04192	-0,14672	7,8142
ETH	0,00466	0,00102	-0,42346	0,33660	0,05648	0,39799	6,5448
XLM	0,00599	-0,00129	-0,33637	1,06091	0,08734	4,0160	39,041
LTC	0,00415	0,00000	-0,36174	0,66587	0,06287	1,8419	15,957
DOGE	0,00436	0,00000	-0,38919	0,61157	0,06795	2,0562	16,576
XMR	0,00331	0,00129	-0,38994	0,53773	0,05981	0,76426	8,7659
XEM	0,00575	0,00042	-0,30325	1,70588	0,08436	6,7043	119,26
XRP	0,00552	-0,00157	-0,46010	1,79396	0,08760	7,3918	129,73
CCi30	0,003231	0,00439	-0,38398	0,19521	0,04544	-0,62303	5,9661
CSAD	0,02565	0,01812	0,00302	0,39219	0,02570	4,9009	43,240

Table 7: Descriptive statistics of Daily Returns from 02/01/2017 to 01/01/2021

All cryptocurrencies are positively skewed, with exception of Bitcoin, and non-normally distributed. The market proxy CCi30 exhibits a positive average daily of around 0,3%, the daily volatility, extracted from the Standard Deviation measure presents a value of around 4,5%, and is moderately negatively skewed, with a value of -0,62 meaning the daily return distribution of the market is more concentrated on the left side of the tails. The Kurtosis values on this case can be characterised as leptokurtic, since it has a higher value than 3 (5,96), suggests that the distribution of the daily CCi30 returns is longer and fatter on the tails.

The variable CSAD on the other hand, show a high positive skewness value 4,90 respectively), indicating that their distribution is more concentrated on the right side of the tails. Kurtosis wise, shows extreme positive values 43,24 relating to fatter tails and more deviations from the mean. Additionally, the standard deviation of CSAD values indicates fairly low cross-sectional variations.

Following the discussion of the models used to test the presence of herding in the previous chapter, it should be expected that if herding exists in the cryptocurrency market, the situation will be observable by the presence of a nonlinear relationship between the dispersion of returns and the market, but his needs to be confirmed through the application of the models.

4.3 Empirical tests

4.3.1 Is Herding Present in the Cryptocurrency market

To test the first hypothesis (H_1: Herding behaviour is present in the Cryptocurrency Market), the CSAD model of Chang et al. (2000) was used, as well as the variation of Chiang and Zheng (2010) to verify the robustness of the results.

Herding presence is tested through the using the upper mentioned equations (i) and (ii) and results extracted from the model are displayed in the following table 8:

	Coef.	**Std. Error**	**t-stat.**	**p-value**	**Adj. R-squared**
Intercept	0,0158	0,0010	15,5274	0,0000***	0,1060
y_1	0,3698	0,0355	10,3890	0,0000***	
y_2	-0,8846	0,2033	-4,3509	0,0000***	

Table 8: Regression of equation (ii). Estimates of herding behaviour in the Cryptocurrency Market.
Regression Model: $CSAD_t = \alpha + \gamma_1 |R_{m,t}| + \gamma_2 R_{m,t}^2 + \varepsilon^t$
*** represents statistical significance at the 5% level.

For all the sample period it is possible to detect a positive coefficient on the linear term γ_1. This suggests that cross-sectional absolute dispersion of returns increases in conjunction with the market. But from the non-linear term γ_2, the coefficient is negative and extremely significant. Meaning that the increase of cross-sectional absolute dispersion of returns increases at a disproportional rate than that of the cryptocurrency market, suggesting strong presence of herding behaviour.

For the purpose of revalidating the results, Herding presence is also tested through the equation (iii). The results extracted from the model are displayed in the following table 9:

	Coef.	**Std. Error**	**t-stat.**	**p-value**	**Adj. R-squared**
Intercept	0,0161	0,0009	16,3242	0,0000***	0,1592
y_1	0,1361	0,0139	9,7570	0,0000***	
y_2	0,3165	0,0349	9,0616	0,0000***	
y_3	-0,4445	0,2022	-2,1986	0,0280*	

Table 9: Regression of equation (iii). Estimates of herding behaviour in the Cryptocurrency Market.
Regression Model: $CSAD = \alpha + y_1 R_{m,t} + y_2 \left|R_{m,t}\right| + y_3 R^2{}_{m,t} + \varepsilon_t$
*** represents statistical significance at the 5% level.

The results confirm the presence of herding, through the coefficient y_3 , which is negative statistically significant.

Therefore, it is possible to conclude that during periods of moderately large movements in market prices investors exhibit herding behaviour, with a high degree of confidence.

4.3.2 Herding intensity under asymmetric conditions

To test the second hypothesis (H2: Herding intensity depends on market returns asymmetry), CSAD model for verifying herding during upwards (downward) market trends was applied through the use of the equations (iv and v).

The results are displayed in the following table 10 for upward movements and for downward movements in the table 11 bellow:

	Coef.	Std. Error	t-stat.	p-value	Adj. R-squared
Intercept	0,0126	0,0005	23,7491	0,0000***	0,5669
γ_1^{UP}	0,6906	0,0173	39,8749	0,0000***	
γ_2^{UP}	-2,8211	0,1964	-14,3611	0,0000***	

Table 10: Regression of equation (v). Estimates of herding behaviour asymmetry in the Cryptocurrency Market.
Regression Model: $CSAD_t^{UP} = \alpha + \gamma_1^{UP}|R_{m,t}^{UP}| + \gamma_2^{UP}(R_{m,t}^{UP})^2 + \varepsilon^t$
*** represents statistical significance at the 5% level.

	Coef.	Std. Error	t-stat.	p-value	Adj. R-squared
Intercept	0,0248	0,0008	30,9368	0,0000***	0,0016
γ_1^{DOWN}	0,0491	0,0323	1,5213	0,0000***	
γ_1^{DOWN}	-0,0210	0,1917	-0,1096	0,9127	

Table 11: Regression of equation (vi). Estimates of herding behaviour asymmetry in the Cryptocurrency Market.
Regression Model: $CSAD_t^{DOWN} = \alpha + \gamma_1^{DOWN}|R_{m,t}^{DOWN}| + \gamma_2^{DOWN}(R_{m,t}^{DOWN})^2 + \varepsilon^t$
*** represents statistical significance at the 5% level.

For periods of large price movements, its possible to observe that the non-linear term γ_2 that captures herding behaviour is negative and statistically significant for upward market trends and negative but not statistically significant for downward market trends, since it shows a p- value of 0,9127 which is superior to the degrees of freedom of 5%.

Additionally, in order to confirm the above results and provide additional robustness, the Chiang and Zheng (2010) model variation for calculation of herding asymmetries given by equation (vi) was applied. The results extracted from the model is displayed in the following table 12:

	Coef.	Std. Error	t-stat.	p-value	Adj. R-squared
Intercept	0,0150	0,0010	14,5178	0,0000***	0,1681
y_1	0,6018	0,0548	10,9721	0,0000***	
y_2	-0,1703	0,0395	-4,3093	0,0000***	
y_3	-1,9003	0,4561	-4,1658	0,0000***	
y_4	-0,2446	0,2090	-1,1701	0,2421	

Table 12: Regression of equation (vi). Estimates of herding behaviour asymmetry in the Cryptocurrency Market.
Regression Model: $CSAD = y_0 + y_1(1 - D^{\mathrm{mt}})|R_{m,t}| * + y_2 D^{\mathrm{mt}}|R_{m,t}| + y_3(1 - D^{\mathrm{mt}})R^2{}_{m,t} + y_4 D^{\mathrm{mt}} R^2{}_{m,t} + \varepsilon_t,$
D is a dummy variable that assumes a value of 1 when $R_{m,t} < 0$, and 0 otherwise.
*** represents statistical significance at the 5% level.

The table 12 above presents the results of herding intensity under asymmetric market conditions (during upwards or downwards movements).

By analysing the results, it is possible to infer that the coefficient y_3 relative to $(1 - D^{\mathrm{mt}})R^2{}_{m,t}$ is negative and statistically significant, meaning herding is present in the cryptocurrency market during periods of positive returns of the market. The coefficient y_4 associated with the dummy variable D^{mt} of bearish market movements, is negative and similarly to the previous model the results were not statistically significant.

Therefore, it is possible to infer that investors tend to herd in a more predominant way during upward rallies of cryptocurrency prices, and since the coefficient y_3 is smaller than y_4 the intensity of herding is also estimated to be more pronounced during upward market trends periods.

4.4 Discussion of the obtained results

It is verified from the dates of 1st of January of 2017 to the 1st of January of 2021, that the eight chosen cryptocurrencies and the market index CCi30 present great volatility. With daily prices reaching plateaus of multiple times over their lowest price during the years, and returns increasing as much as almost 180% in one day for some cryptocurrencies or decreasing almost 50%.

Seeing the high volatile characteristics of the cryptocurrency market, it is tested the hypothesis that herding behaviour is significantly present in the market and whether herding behaviour is found to be more intense during upward or downward market movements.

4.4.1 Discussion of Hypothesis 1 results

The results extracted from the application of the CSAD models devised by Chang et al. (2000) and Chiang and Zheng (2010) validate Hypothesis 1, that herding is significantly present in the cryptocurrency market.

For the first model, the behaviour was detected by a statistically significant negative coefficient of the term γ_2. And for the second, by the term γ_3 which was also negative and statistically significant, although slightly less evident (p-value less significant). This less statistically significant result derives from the use of a third term, ($R_{m,t}$), to the original Chang et al. (2000) equation which takes care of the asymmetry between stock return dispersion and the market's return.

Overall, the results confirm this study expectations that herding is significantly present in cryptocurrency market not by random chance alone. Corroborating the findings of Ajaz and Kumar (2018), Kallinterakis and Wang (2019), Tomàs (2019), Ballis and Drakos (2020), Kyriasis (2020), Jalal et al. (2020), Senarathne and Jianguo (2020) and Yousef (2020).

These results, having in mind all the literature reviewed and the context of the sample of this study, indicate the existence of both types of herding (spurious and intentional).

One because cryptocurrency prices seem to fluctuate around relevant news such as accumulated hacks, regulatory constraints and technological advancements. Indicating that investors are essentially reacting to similar information and environment. But on the other hand, and in my view most important, the cryptocurrency seems to herd intentionally on the grounds of informational biases. Meaning that power of the masses behind this market has an incredible reach. Leading specially less informed and novice investors to imitate the market in the hope of not missing out on the opportunity.

4.4.2 Discussion of Hypothesis 2 results

By verifying the presence of herding behaviour, the "stage" was set to conduct tests on the second hypothesis regarding herding intensity during asymmetric market periods. Again, the tests used the most powerful methodologies for empirical herding detection of Chang et al. (2000) and Chiang and Zheng (2010). Being that the application of the second model was employed solely for robustness.

The hypothesis 2 was verified only for bullish market movements. While on downward periods although herding was verified by the negative coefficients (γ_2^{DOWN};y_4) but the results were not statistically significant.

Additionally, since the coefficients (γ_2^{UP};y_3) for upward market movements in both models were more negative than those of the downward coefficients, meant that herding is clearly more intense during bullish moments of the cryptocurrency market.

These results are rather unexpected since most reviewed literature on herding points it to be more intense during downward moments. And therefore, the expectations of this empirical tests were only half validated.

When comparing with the reviewed empirical literature, these results are consistent with the findings of Kallinterakis and Wang (2019), Ballis and Drakos (2020) and Kyriasis (2020), which used the same CSAD model with different samples of cryptocurrencies. And differing to the findings of Thomàs (2019) which tests shows herding in the cryptocurrency to be more intense during downward price movements.

Additionally, literature points in the direction that large upward movements in the cryptocurrency prices have their motivations on intentional herding behaviour due to the impact of social dynamics on these assets. Which was discussed to be largely inconsistent with the Efficient Market Hypothesis of Fama. Meaning that the cryptocurrency market is more likely to operate on inefficient and irrational standards especially when there is a bullish trend.

Chapter 5
Conclusion

5.1 Main conclusions

This study empirically tested the possibility of existing herding in the cryptocurrency market as well as its intensity across different market conditions, using the cross-sectional models of returns developed by Chang et al. (2000) and Chiang and Zheng (2010). Daily returns of eight major capitalized cryptocurrencies and the market index CCi30 were used from the periods of the 1st of January of 2017 to the 1st of January 2021 to capture this behaviour.

The results obtained from the models found herding behaviour to be present in the cryptocurrency market, with more intensity during bullish market periods. Revealing investors irrational inclination towards expectations of future prices of cryptocurrencies.

These results support the theory that the attitude of investors towards cryptocurrencies is driven by sentiments of euphoria, not missing out on an opportunity and reactions to social networks news, which have been shown to have had an increasing impact on this market. Even though the market has shown signs of ruptures in the past (e.g. market crash of early 2018), investors seem to be less risk averse in this market, and trade to a massive extent often in conformity to the market, on the speculation of gains from a bullish trend.

This is also indicative of intentional herding on the form of informational cascades. Where investors further on the chain of are pushed to follow the crowd due to the massification of beliefs. This behaviour can be highly complex, but generally it is interpreted as irrational and inconsistent to the Efficient Market Hypothesis, proving that investors do not always make decisions based on rational and mathematical thoughts.

Lastly this study offers relevant academic insights on herding behaviour in emerging technological markets. And it should also be taken into consideration when investigating the functioning of the cryptocurrency market as well as other markets with speculative traits.

5.2 Implications for management

With the cryptocurrency market growing in size and popularity, there are several important notions to address to the key participants of this market in order for them to be able to better manage its risks.

For sophisticated investors which often trade cryptocurrencies against fiat currencies in digital exchange platforms, this study endorses the introduction of herding patterns in prediction models. This may allow better identification of market trends and ultimately increase the probabilities of profit.

Additionally, cryptocurrencies should be used as a means of diversification to compensate for sharp downturns of other markets, like it was verified during the pandemic year of 2020.

For other investors that are new to this market, they should get more informed about cryptocurrency fundamentals such as their technology, supply limitations and their risks regarding regulations, climate impacts. By doing so, this market can instead move towards efficiency levels instead of being influenced by the sentiment of the and social media platforms/forums such as Reddit.

In the presence of strong evidence of herding behaviour in the market, policymakers should develop appropriate strategies to keep cryptocurrencies at a consistent level preventing bubble formation events. This is easier said than done, especially since the cryptocurrency market is severely deregulated.

Additionally, since this market is often connected to fraud and money laundering schemes which means that governments, financial institutions, and legal entities have a handful of issues in their hands. In that sense, regulatory institutions by developing a tailored framework for cryptocurrencies, could bring some stability/normality to the market.

Some policy recommendations in the face of these issues, could be the mandatory registration of users unveiling their anonymity or by ban of certain aspects surrounding cryptocurrencies that are aimed at anonymity. Extending the scope of funds transfer, allowing a tracking of transactions, and therefore controlling money laundering and financial terrorism.

These policies on the other hand defeat the purpose of cryptocurrencies which is highly linked to the decentralization and anonymity and it is unlikely to be well welcomed by investors in the market.

For coin inventors, this research can be interesting tool as to help designing or improving a cryptocurrency code in a way that it can incorporate the speculative traits of the market and human sentiment. Also, and having in mind the ecological impact of these assets due to the "mining" process, it should be relevant for these inventors to think of ways of minimizing the computational power and energy needed to process a transaction/block on the chain.

5.3 Limitations of research

Throughout the last decades the world has seen an emergence of new technology, and information is circulating faster and faster.

When it comes to cryptocurrencies and its technology, they also seem to be expanding at an incredible rate therefore it is difficult for researchers to keep up with its advancements. Moreover, since the market is fairly new, information is very dispersed and not completely solid.

Investors, institutions and governments are still finding how to react to the development of this market, with new policies gradually taking place and new ways of using cryptocurrencies surging. This continuous change makes it difficult for comprehension.

Other limitations of this study lie in the are numerous complexities to the human behaviour, in which models still cannot fully account for all of them. In particular, the models used in this study serve the purpose of capturing the behaviour, but the task is complicated when trying to explain it.

Therefore, achieving a precise answer on what motivates investors decisions from a herding perspective is a though challenge.

5.4 Future research

Research in the near future should increase its attention in explaining the motivations behind the occurrence of herding behaviour in the cryptocurrency market. A handful of studies examined the existence of herding, but only few pointed in a direction of what makes herding a prevalent behaviour in this market. Additionally, while this study approaches the models devised by Chang et al. (2000) and Chiang and Zheng (2010) to measure herding, and the application of alternative models might give additional insights or even allow the prediction of the market direction.

Another hypothesis for research in the cryptocurrency market could be the distinction between the different types of herding (spurious or intentional). Which although through the literature review of this study, intentional herding seems to be more strong, empirical tests on this matter could provide additional information and confirmation on whether the herding of investors is based on a rational thought process or merely following the markets' opinion and disregarding their own information. This is important because it gives an insight on if the cryptocurrency market behaves in an efficient or inefficient manner.

Future research should also encompass more cryptocurrencies more recent data, which hasn't yet been target of studies.

Bibliography

1. Avery, C. & Zemsky, P. 1998. Multidimensional Uncertainty and Herd Behaviour in Financial Markets. American Economic Review, 88: 724-748.
2. Ajaz, T. & Kumar, A. 2018. Herding in Crypto-currency markets. Annals of Financial Economics. Vol. 13, No. 02, 1850006.
3. American Institute for Economic Research. Earle, P., 2021. Ten remarkable events of 2020. Available at: https://www.aier.org/article/ten-remarkable-financial-events-of-2020/. (01/01/2021).
4. Amirat, A., & Alwafi, W. 2020. Does herding behavior exist in cryptocurrency market? Cogent Economics & Finance, 8: 1, 1735680.
5. Bachelier L. 1900. Theory of speculation. A thesis presented to the Faculty of Sciences of the Academy of Paris on March 29, 1900. Originally published in Annales de l'Ecole Normale Supérieure, 27, 21-86.
6. Baek, C. & M. Elbeck. 2015. Bitcoins as an investment or speculative vehicle? A first look. Applied Economics Letters, 22: 1, 30–34.
7. Ballis, A. & Drakos, K. 2020. Testing for herding in the cryptocurrency market. Finance Res. Lett., 33, p. 101210
8. Banerjee, V. 1992. "A Simple Model of Herd Behavior", The Quarterly Journal of Economics, Vol. CVII, 3: 797-817.
9. Barberis, N. & Thaler, R. 2003. "A Survey of Behavioral Finance" Handbook of the Economics of Finance (edited by G. M. Constantinides, M.Harris and R. Stulz), Elsevier Science B.V., pp. 1053- 1123.
10. Barberis, N. 2017. Behavioural Finance: Asset Prices and Investor Behavior. American Economic Association. New Haven, CT: Yale University.

11. BenSaïda, A. 2017. Herding effect on idiosyncratic volatility in US industries. Finance Res. Lett., 23, pp. 121-132

12. Bhidé, A. 2010. A Call for Judgment: Sensible Finance for a Dynamic Economy. October 21. Oxford University Press, Inc.

13. Bhosale, J., & Mavale, S. 2018. Volatility of select Crypto-currencies: A comparison of Bitcoin Ethereum and Litecoin. Annu. Res. J. SCMS, Pune, vol 6.

14. Bikhchandani, S., Hirshleifer, D. & Welch, I.1992. A Theory of Fads, Fashion, Custom, and Cultural Change as Informational Cascades. Journal of Political Economy, Vol. 100, No. 5, 992-1026.

15. Bikhchandani S. & Sharma S. 2001. Herd Behaviour in Financial Markets, IMF Staff Papers, 47, 3.

16. Böhme, R., Christin, N., Edelman, B., & Moore, T. 2015. Bitcoin: Economics, technology, and governance. Journal of economic Perspectives, 29: 2, 213-38.

17. Borch, C. 2016. High-frequency trading, algorithmic finance and the flash crash: Reflections on eventalization. Economy and Society, 45: 3-4, 350-378.

18. Borensztein, R. & Gelos, G. 2003. A Panic Prone Pack? The Behavior of Emerging Market Mutual Funds, in IMF Staff Papers, Vol. 50, No. 1.

19. Bouoiyour, J. & Selmi, R. 2014. What Does Crypto-currency Look Like? Gaining Insight into Bitcoin Phenomenon. SSRN working paper. MPRA Paper No: 57907.

20. Bouri, E., Gupta, R., & Roubaud, D. 2019. Herding behaviour in cryptocurrencies. Finance Research Letters, 29, 216-221.Bratspies, M. 2018. Cryptocurrencies and the Myth of the Trustless Transaction, 6-7.

21. Brito, J., & Castillo, A. 2013. Bitcoin: A primer for policymakers. Mercatus Center at George Mason University. 422.

22. Brunnermeier, K. 2008. Bubbles. In Palgrave Macmillan, eds. The New Palgrave Dictionary of Economics. Palgrave Macmillan, London.

23. Bui, N., Nguyen, L., Nguyen, N. & Titman, G. 2018. Herding in frontier stock markets: Evidence from the Vietnamese stock market. Account Finance, 58: S1, 59–81.

24. Bukovina, J, & M Martiček. 2016. Sentiment and Bitcoin volatility. Mendelu Working Papers in Business and Economics 2016-58. Mendel University in Brno, Faculty of Business and Economics.

25. Business Insider. Martin, W. 2017. The 15 charts that defined the global economy in 2017. Available at: https://www.businessinsider.com/15-charts-2017-in-the-global-economy-2017-12. (13/12/2017; 07h 00m).

26. Buterin, V. (2016). What is Ethereum?. Ethereum Official webpage, available at: https://ethereum.org/en/whitepaper/

27. Cai F., Han, S., Li D. & Li Y., 2019.Institutional herding and its price impact: evidence from the corporate bond market. J. Financ. Econ., 131: 1, pp. 139-167.

28. Cakan, E., Demirer, R, Gupta, R. & Marfatia. H. 2019. Oil speculation and herding behavior in emerging stock markets. J. Econ. Finance, 43: 1, pp. 44-56.

29. Calderón, O. P. Cryptocurrency markets meets behavioral economics: Biases and herding.

30. Çelen, B., & Kariv, S. 2004. Distinguishing informational cascades from herd behavior in the laboratory. American Economic Review, 94:3, 484-498.

31. Chang, E. C., Cheng, J. W., & Khorana, A. 2000. An examination of herd behavior in equity markets: An international perspective. Journal of Banking & Finance, 24:10, 1651-1679.

32. Chauhan, Y., Ahmad, N., Aggarwal, V. & Chandrad, A. 2019. Herd behavior and asset pricing in the Indian Stock Market. IIMB Management Review, 0–25.

33. Cheah, T. & Fry, J. 2015. Speculative bubbles in Bitcoin markets? An empirical investigation into the fundamental value of Bitcoin. Economics Letters. vol. 130, C, 32-36.

34. Chen, Z. & Lux, T. 2018. Estimation of sentiment effects in financial markets: a simulated method of moments approach Comput. Econ., 52: 3, pp. 711-744.

35. Chen, Z. & Ru J.2019. Herding and capitalization size in the Chinese stock market: a micro-foundation evidence Empir. Econ. pp. 1-17

36. Chiang, C. &. Zheng, D. 2010. An empirical analysis of herding behaviour in global stock markets. Journal of Banking and Finance, 34:8, 1911–1921.

37. Chohan, W. 2017. A history of Dogecoin. Discussion Series: Notes on the 21st Century.

38. Christie, G. & Huang, D. 1995. Following the pied piper: do individual returns herd around the market? Financial Analysts Journal, 51, 31–37.

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

40. De Bondt, M. & Thaler, R.. 1985. “Does the Stock Market Overreact?” Journal of Finance. July, 40, pp. 793–805.

41. De Bondt, M. & Teoh, L. 1997. Herding behavior and stock returns: an exploratory investigation. Swiss Journal of Economics and Statistics 133, 293-324.

42. De Long, B., Shleifer, A., Summers, L. & Waldmann, R. 1990. Positive Feedback Investment Strategies and Destabilizing Rational Speculation. The Journal of Finance 45: 2, 379–95

43. Demirer, R., Kutan, M. & Chen, D. 2010. Do investors herd in emerging stock markets?: evidence from the Taiwanese market. J. Econ. Behav. Organ., 76: 2, pp. 283-295

44. Deng, X., Hung, S. & Qiao, Z. 2018. Mutual fund herding and stock price crashes. J. Bank. Finance, 94, pp. 166-184

45. Devenow, A. & Welch, I. 1996. Rational Herding in Financial Economics. European Economic Review, 40, 603-615.

46. Dow, J., & Gorton, G. 1994. Arbitrage chains, Journal of Finance 49, 819-849.

47. Dreman, D. 1979. Preferences for stock Characteristics as revealed by mutual fund portfolio holdings, Journal of Finance 51, 111-135.

48. Dwyer, P. 2015. The economics of Bitcoin and similar private digital currencies. Journal of Financial Stability 17, 81-91.

49. Dyhrberg, H. 2016. Bitcoin, gold and the dollar–A GARCH volatility analysis. Finance Research Letters 16, 85-92.

50. Ecb virtual currency schemes report. October 2012. Available at: https://www.ecb.europa.eu/pub/pdf/other/virtualcurrencyschemes201210en.pdf.

51. ECB, "Virtual Currency Schemes – a further analysis", February 2015. Available at: https://www.ecb.europa.eu/pub/pdf/other/virtualcurrencyschemesen.pdf, 7.

52. Economou, F., Kostakis, A. & Philippas, N. 2011. Cross-country effects in herding behaviour: Evidence from four south European markets. Journal of International Financial Markets, Institutions and Money 21. 3, 443 – 460.

53. Edwards, S. 1999 : Contagion, Paper presented at the 1999 World Economy Lecture, University of Nottingham.

54. Evans, G. 1991. Pitfalls in Testing for Explosive Bubbles in Asset Prices. American Economic Review, 81:4, 922-30.

55. Fama, E. 1965. The Behavior of Stock-Market Prices. The Journal of Business, 38:1, 34-105.

56. Fama, E. 1965. Random Walks in Stock Market Prices. Selected Papers of the Graduate School of Business, University of Chicago, Reprinted in the Financial Analysts Journal, September-October 1965; The Analysts Journal, London, 1966; The Institutional Investor, October 1968, 55-59.

57. Fama E. 1970. Efficient Capital Markets: A Review of Theory and Empirical Work. The Journal of Finance, vol.25, no. 2

58. Fama, E. (1991). Eficient Capital Markets II. Volume 46, Issue 5. Pg. 1576

59. Forbes. Carson, R. 2018. A look back at 10 of the top financial news stories of 2018. Available at: forbes.com/sites/rcarson/2018/12/23/a-look-back-at-10-of-the-top-financial-news-stories-of-2018/?sh=57e93943bd1d. (23/12/2018; 13h 08m).

60. Fox, J. 2009. The myth of the rational market: A history of risk, reward, and delusion on Wall Street. New York: Harper Business.

61. Friedman, M. 1984. A comment: Stock prices and social dynamics, Brookings Papers on Economic Activity 2, 504-508.

62. Fry, J & Cheah, T. 2016. Negative bubbles and shocks in cryptocurrency markets. International Review of Financial Analysis 47, 343-352.

63. Garcia, D., Tessone, 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: 99, 20140623.

64. Garcia, D. & Schweitzer, F. 2015. Social Signals and Algorithmic Trading of Bitcoin, Royal Society Open Science, 2, pp. 1–13.

65. Gibbs, T., & Yordchim, S. 2014. Thai perception on Litecoin value. International Journal of Social, Behavioral, Educational, Economic, Business and Industrial Engineering, 8:8, 2613-5.

66. Gleason, C., Lee I., Mathur I. 2003. Herding behavior in European futures markets. Fin Letters. 1:5-8.

67. Godsiff, P. 2015. Bitcoin: Bubble or Blockchain? In 9th International KES Conference on Agents and Multi-Agent Systems: Technologies and Applications KES-AMSTA-15

68. Graham, R., 1999. "Herding Among Investment Newsletters: Theory and Evidence", The Journal of Finance, Vol. LIV, No. 1, 237-268.

69. Grossman, J. & Joseph E. Stiglitz. 1980. "On the Impossibility of Informationally Efficient Markets." American Economic Review. 70:3, pp. 393–408.

70. Gruber, M. 1996. Another Puzzle: The growth in Actively managed Mutual funds. Journal of Finance 51, 783-810.

71. Guillaume, F., & Linders, D. 2015. Stochastic modelling of herd behaviour indices. Quantitative Finance, 15:12, 1963-1977.

72. Haugen, A. & Lakonishok, J. 1988. The Incredible January Effect. Homewood: Dow Jones-Irwin.

73. Hinteregger, A., & Haslhofer, B. 2018. An empirical analysis of monero cross-chain traceability. arXiv preprint arXiv:1812.02808.

74. Hirshleifer, D., Subrahmanyam, A. & Titman, S. 1994. Security analysis and trading patterns when some investors receive private information before others, Journal of Finance 49, 1665-1698.

75. Hirshleifer, D. 2001. Investor Psychology and Asset Pricing. Journal of Finance, Vol. LVI, No4, 1533- 1598.

76. Hirshleifer, D. & Teoh, H. 2003. Herd Behaviour and Cascading in Capital Markets: A Review and Synthesis. Fisher College of Business, The Ohio State University. Eur. Financ. Manag., 9: 1, pp. 25-66

77. Hossein, A. (2020). Excel For Statistical Data Analysis.

78. Houben, R. 2015. Bitcoin: there two sides to every coin. ICCLR, Vol. 26, 5, 195.

79. Huddart, S. 1996. Reputation and performance fee effects on portfolio choice by investment advisors, Working paper, Duke University.

80. Hudson, S., & Gregoriou, A. 2015. Calculating and comparing security returns is harder than you think: A comparison between logarithmic and simple returns. International Review of Financial Analysis, 38, 151-162.

81. Hwang, S. and Salmon, M. 2003. Market Stress and Herding Journal of Empirical Finance, 11: 4, 585-616.

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

83. Javaira, Z., & Hassan, A. 2015. An examination of herding behavior in Pakistani stock market. International Journal of Emerging Markets, 10:3, 474-490.

84. Jayachandran, P. 2017. The difference between public and private blockchain. Blockchain Unleashed: IBM Blockchain Blog, 2017.

85. Jensen, Michael C. 1968. The performance of mutual funds in the period 1945–1964, Journal of Finance 23, 389–416

86. Jensen, M. 1978. Some Anomalous Evidence Regarding Market Efficiency. Journal of Financial Economics, Vol.6, Nos. 2/3 , 95-101.

87. Kahneman, D. & Tversky, A. 1979. Prospect Theory: An Analysis of Decision Under Risk. Econometrica. 47:2, pp. 263–91.

88. Kahneman, D. & Riepe, M.1998. “Aspects of Investor Psychology.” Journal of Portfolio Management. Summer, 24:4, pp. 52–65.

89. Kallinterakis, V. & Wang, Y. 2019. Do investors herd in cryptocurrencies–and why? Res. Int. Bus. Finance, 50, pp. 240-245

90. Kaminsky, G., Reinhart C. 2000. On Crises, Contagion and Confusion, in: Journal of International Economics, Vol. 51, No. 1, pp. 145-163.

91. Karceski, J. 2002. Returns-chasing behavior, mutual funds, and beta's death. Journal of Financial and Quantitative analysis, 559-594.

92. Keim, D. B. 1983. Size-related anomalies and stock return seasonality: Further empirical evidence. Journal of financial economics, 12:1, 13-32.

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

94. Konow, J. 2000. Fair Shares: Accountability and Cognitive Dissonance in Allocation Decisions. Digital Commons at Loyola Marymount University and Loyola Law School

100. Kristoufek, L. 2015. What are the main drivers of the bitcoin price? Evidence from wavelet coherence analysis. PLoS ONE 10:4, pp. 1–15

101. Kumar, S., & Goyal, N. 2016. Evidence on rationality and behavioural biases in investment decision making abstract. Q. Res. Financial Mark. 8, 270–287.

102. Kyriazis, N., Papadamou, & Corbet, S. 2020. A systematic review of the bubble dynamics of cryptocurrency prices. Research in International Business and Finance, Volume 54.

103. Kyriazis, N. 2020. Herding behaviour in digital currency markets: An integrated survey and empirical estimation, Heliyon, Volume 6, Issue 8.

104. Lakonishok, J., Shleifer, A., Thaler, R. & Vishny, R. 1991, Window dressing by pension fund managers, American Economic Review, Papers and Proceedings 81, 226-231.

105. Lakonishok, J., Shleifer, A. & Vishny, R. 1992. The impact of institutional trading on stock prices. Journal of Financial Economics 23, 23-43.

106. Lakonishok, J., Shleifer, A. & Vishny, R. 1994. Contrarian Investment, Extrapolation, and Risk. Journal of Finance, vol. 49, no. 5 (December):1541–1578.

107. Lee, C., Chen, P. & Hsieh, M. 2013. Industry herding and market states: evidence from Chinese stock markets. Quant. Finance, 13: 7, pp. 1091-1113.

108. Lee, Y., Liao, T. & Hsu, C. 2015. The Impact of Macroeconomic Factors on the Herding Behaviour of Investors. Asian Economic and Financial Review, 5:2, 295-304

109. Li, X. & Wang, A. 2017. The technology and economic determinants of cryptocurrency exchange rates: The case of Bitcoin. Decision Support Systems 95, pp. 49–60.

110. Lindhe E. 2012. Herd behavior in stock markets a Nordic study.

111. Liu, Y. & Tsyvinski, A. 2018. Risks and Returns of Cryptocurrency. National Bureau of Economic Research, working paper 24877.

112. Lokhava, M., Losa, G., Mazières, D., Hoare, G., Barry, N., Gafni, E. & McCaleb, J. 2019. Fast and secure global payments with stellar. In Proceedings of the 27th ACM Symposium on Operating Systems Principles. pp. 80-96.

113. Loomes, G. & Robert, S. 1982. Regret Theory: An Alternative Theory of Rational Choice Under Uncertainty. The Economic Journal 92, 805-824.

114. Loomes, G. 1987. Some Implications of a More General Form of Regret Theory. The Journal of Economic Theory 41, 270-287.

115.Lorenzoni, G. 2008. Inefficient credit booms. The Review of Economic Studies, 75: 3, 809-833.

116. Mai, F., Shan, Z., Bai, Q., Wang, X., & Chiang, R. H. 2018. How Does Social Media Impact Bitcoin Value? A Test of the Silent Majority Hypothesis. Journal of Management Information Systems. 35:1, pp. 19–52.

117. Malkiel B. 2003. The Efficient Market Hypothesis and its Critics. Journal of Economic Perspectives – Volume 17, Number I – winter 2003 – Pages 59-82;

118. Malkiel, B. 2011. The efficient-market hypothesis and the financial crisis. Rethinking Finance: Perspectives on the Crisis (Proceedings of a Conference). Russel Sage Foundation.

119. McAleer, M. & K. Radalj, K. 2013. Herding, information cascades and volatility spillovers in futures markets. J. Rev. Global Econ., 2, pp. 307-329

120. Mehra, R., & Prescott, E. 1985. "The Equity Premium: A Puzzle." Journal of Monetary Economics, vol. 15, no. 2 (March):145–161.

121. Mélard, G. 2014. On the accuracy of statistical procedures in Microsoft Excel 2010. Computational statistics, 29:5, 1095-1128.

122. Modigliani, F., and M.H. Miller. 1958. "The Cost of Capital, Corporate Finance and the Theory of Investment." American Economic Review, vol. 48, no. 3 (June):261–297.

123. Miller, M. 1991. Financial Innovations and Market Volatility. (pp. 1-288). Cambridge, MA: Blackwell.

124.Morgenstern, O. & Granger, C. 1970. Predictability of stock market prices. Lexington, MA: DC Heath.

125. Nadarajah, S & Chu, J. 2017. On the inefficiency of Bitcoin. Economics Letters 150, 6-9.

126.NASDAQ. Mason, B., 2019. Events that shook the global financial market in 2019. Available at: https://www.nasdaq.com/articles/events-that-shook-the-global-financial-markets-in-2019-2019-12-29. (29/12/2019; 07h 40m).

127.Natarajan, H., Krause, S. and Gradstein, H. World Bank Group "Distributed Ledger Technology (DLT) and blockchain", 2017, FinTech note, no. 1. Washington, D.C.

128. Nofsinger, R., & Sias, W. 1999. Herding and feedback trading by institutional and individual investors. The Journal of finance, 54:6, 2263-2295.

129. Obeng, G. 2020. Behavioural finance; a concept or catalyst explaining distortions in investment decision. Eur. J. Bus. Manag. Res. 5, 1–13.

130. Ofek, E., & Richardson, M. P. 2001. DotCom mania: a survey of market efficiency in the internet sector. Available at SSRN 268311.

131.Patterson, D. M. & Sharma, V. 2005. Intraday Herding and Market Efficiency, Working Paper, University of Michigan-Dearborn.

132.Pindyck, S. & Rotemberg, J. 1990. The excess Co-movement of commodity prices. Econ. J., 100. 403, pp. 1173-1189.

133.Pochea, M., Filip, M., & Pece, M. 2017. Herding behavior in CEE stock markets under asymmetric conditions: A quantile regression analysis. Journal of Behavioral Finance, 18:4, 400-416.

134.Poincaré 1908. The value of science. Dover Publications.

135. Pompian, M. 2012. Behavioural Finance and Investor Types: Managing Behavior to Make Better Investment Decisions. Hoboken, NJ: John Wiley & Sons.

136. Poyser, O. 2017. Exploring the determinants of Bitcoin's price: an application of Bayesian Structural Time Series. Dissertation.

137. Prechter Jr, R. 2001. Unconscious herding behavior as the psychological basis of financial market trends and patterns. The Journal of Psychology and Financial Markets, 2:3, 120-125.

138. Quasim, T., Khan, A., Algarni, F., Alharthy, A. & Alshmrani, M. 2020. Blockchain Frameworks. In Decentralised Internet of Things (pp. 75-89). Springer, Cham.

139. Rabelais M. 1552. Qvart Livre. Des faicts et dicts heroiques du bon Pantagruel.

140. Read, C. (2012). The Efficient Market Hypothesists.

141. Revenda, Z., Mandel, M., Kodera, J., Musílek, P., Dvorak, P., & Brada J. Praha: Management Press, 2005. ISBN 80-7261-132-1.

142. Ritter, J. 2003. Behavioral Finance. Pacific-Basin Finance Journal Vol. 11, No. 4, pp. 429-437

143. Samuelson, Paul A. 1965. Proof That Properly Anticipated Prices Fluctuate Randomly. Industrial Management Review, 6:2 41-49.

144. Scharfstein, S., Stein, J.C., 1990. Herd behaviour and investment. The American Economic Review 80:3, 465-479.

145. Senner, R. 2018. Following Financial Stocks and Flows: Global Imbalances, Financial Crises and Crypto Currencies. PhD Thesis. ETH Zuric.

146. Senarathne, C., & Jianguo, W. 2020. Herd behaviour in the cryptocurrency market: Fundamental vs. spurious herding. The European Journal of Applied Economics, 17: 1, 20-36.

147. Sharma, A., & Kumar, A. 2019. A review paper on behavioural finance: study of emerging trends. Q. Res. Financial Mark. 12, 137–157.

148. Shefrin, H., & Statman, M. 2011. "Behavioural finance in the financial crisis: market efficiency, minsky, and keynes," in Rethinking the Financial Crisis, Working Paper, Santa Clara, CA: Santa Clara University

149. Shleifer, Andrei. 2000. Inefficient markets: An introduction to behavioral finance. New York: Oxford University Press

150. Shilller, R. 1981. "Do Stock Prices Move Too Much to Be Justified by Subsequent Changes in Dividends?" American Economic Review, vol. 71, no. 3 (June) :421–436.

151. Shiller, R. 1984. Stock Prices and Social Dynamics. Brookings Papers on Economic Activity 2, 457-510.

152. Shiller, R. J., 1995. "Conversation, Information and Herd Behavior" American Economic Review, 85: 2, 181–185."

153. Shiller, R. J. 1999. Human behavior and the efficiency of the financial system. In J.Taylor, and M. Woodford, ed.: Handbook of Macroeconomics, Elsevier, Amsterdam.

154. Shiller, R. J. 2000. Irrational Exuberance. Princeton: Princeton University Press.

155. Shiller, R. 2003. From Efficient Markets Theory to Behavioral Finance. Journal of Economic Perspectives. Vol. 17,No. 1, Winter 2003, pp. 83-104.

156. Sias, R. & Nofsinger,J. 1999. Herding and Feedback Trading by Institutional and Individual Investors. Journal of Finance, 54.6: 2263-2295.

157. Sovbetov, Y. 2018. "Factors Influencing Cryptocurrency Prices: Evidence from Bitcoin, Ethereum, Dash, Litcoin, and Monero Journal of Economics and Financial Analysis," Journal of Economics and Financial Analysis. 2:2, pp. 1– 27.

158.Stanovich, K. E., & West, F. 1998a. "Individual differences in rational thought," Journal of Experimental Psychology: General, 127, 161-188.

159. Subrahmanyam, A. 2007. Behavioural Finance: A Review and Synthesis. European Financial Management, Vol. 14, No. 1, 12-29.

160. Tan, L., Chiang, T. C., Mason, J. R. & Nelling, E. 2008. Herding behavior in Chinese stock markets: An examination of A and B shares. Pacific-Basin Finance Journal, 16, 61–77.

161. Taskinsoy, J. 2019. Bitcoin: The Longest Running Mania – Tulips of the 21st Century? Available at SSRN 3505953.

162. Terzi, A. (2016), "A T-shirt model of savings, debt, and private spending: lessons for the euro area", The European Journal of Economics and Economic Policies, Vol. 13 N. 1, pp. 39-56, 2016.

163. Thaler, R. H. & Mullainathan, S. 2000). Behavioral economics (No. w7948). National Bureau of Economic Research.

164. Tikhomirov, S., Voskresenskaya, E., Ivanitskiy, I., Takhaviev, R., Marchenko, E., & Alexandrov, Y. 2018. Smartcheck: Static analysis of ethereum smart contracts. In Proceedings of the 1st International Workshop on Emerging Trends in Software Engineering for Blockchain. pp. 9-16.

165. Timmermann & Granger, 2004. Efficient market hypothesis and forecasting, International Journal of Forecasting. Vol. 20, Issue 1, January–March 2004, Pages 15-27.

166. Tomás, D., Ibáñez, A. & Farinós, J. 2019. Herding in the cryptocurrency market: CSSD and CSAD approaches, Finance Research Letters, Volume 30, Pages 181-186.

167. Trueman, B., 1994, "Analyst Forecasts and Herding Behaviour", The Review of Financial Studies, Vol.7, No.1, 97-124

168. Tversky, A. & Kahneman, D. 1973. Judgment Under Uncertainty: Heuristics and Biases. Office of Naval Research. 185:4157, 1124-1131.

169. Tversky, A. & Kahneman, D. 1979. Prospect Theory: An Analysis of decision under risk. Econometrica, Vol. 47, No2., pp. 263-292.

170. Tversky, A. & Kahneman, D. 1992. Advances in Prospect Theory: Cumulative Representation of Uncertainty. Journal of Risk and Uncertainty, 5:927-323.

171. Urquhart, A (2016). The inefficiency of Bitcoin. Economics Letters 148, 80-82.

172. Voronkova, S. & Bohl, M.T. 2005. Institutional traders' behaviour in an emerging stock market: empirical evidence on Polish pension fund investors. Journal of Business, Finance and Accounting 32:7&8, 1537-1560.

173. Wang, J. 1993. A model of intertemporal asset prices under asymmetric information. The Review of Economic Studies, 60:2, 249-282.

174. Weidmann, J. 2012. "Money creation and responsibility", Speech at the 18th colloquium of the Institute for Bank-Historical Research (IBF) in Frankfurt

175. Welch, I. 2000. "Herding among Security Analysts." Journal of Financial Economics 58: 369–396.

176. West, K. D. 1984. Speculative Bubbles and Stock Price Volatility. Financial Research Memorandum no. 54. Princeton, N.J.: Princeton Univ., December.

177. Witzig, P. & Salomon, V. 2018. "Cutting out the middleman: a case study of blockchain-induced reconfigurations in the Swiss Financial Services Industry", Working Paper 1, the Circulation of Wealth, Université de Neuchâtel, 6-7.

178. Wood, G. 2014. Ethereum: A secure decentralised generalised transaction ledger. Ethereum project yellow paper, 151, 1-32.

179. Yao, J., Ma, C., & He, W. P. 2014. Investor herding behaviour of Chinese stock market. International Review of Economics & Finance, 29, 12-29.

180. Yermack, D. 2015. Is Bitcoin a real currency? An economic appraisal. In Handbook of digital currency, pp. 31-43. Academic Press.

181. Youssef, M. 2020. What Drives Herding Behavior in the Cryptocurrency Market?, Journal of Behavioral Finance, 1-10.

182.Zhou, R., & Lai, R. (2009). Herding and Information based trading. Journal of Empirical Finance, 16(3), 388–393.

Appendix

Tables

Date	BTC	ETH	XLM	DOGE	XRP	LTC	XMR	XEM	CCi30
Max Jan 2017	10,62%	16,11%	18,48%	3,96%	8,61%	7,77%	16,45%	16,43%	11,02%
Min Jan 2017	-14,31%	-8,89%	-11,30%	-9,24%	-5,62%	-16,12%	-13,34%	-8,49%	-11,91%
Max Feb 2017	4,41%	15,62%	6,41%	5,54%	5,55%	1,34%	6,48%	14,71%	3,68%
Min Feb 2017	-6,46%	-3,50%	-5,39%	-5,75%	-6,17%	-5,47%	-7,38%	-10,93%	-5,82%
Max Mar2017	8,18%	32,20%	16,68%	12,48%	44,91%	66,59%	18,44%	37,71%	11,66%
Min Mar 2017	-11,49%	-27,06%	-9,33%	-8,54%	-13,35%	-4,25%	-12,20%	-15,10%	-9,12%
Max Apr 2017	5,15%	17,92%	58,99%	45,97%	179,40%	33,78%	9,50%	33,39%	7,15%
Min Apr 2017	-2,59%	-9,01%	-25,32%	-12,71%	-46,01%	-12,20%	-8,10%	-12,37%	-5,01%
Max May 2017	7,93%	33,66%	106,09%	61,16%	39,77%	32,33%	53,77%	78,49%	10,93%
Min May 2017	-7,43%	-8,21%	-30,67%	-19,04%	-21,82%	-20,57%	-18,41%	-20,99%	-11,61%
Max Jun 2017	6,97%	19,85%	25,68%	21,83%	35,32%	33,47%	15,15%	14,10%	6,84%
Min Jun 2017	-10,09%	-10,08%	-12,91%	-11,73%	-9,08%	-11,20%	-14,75%	-10,34%	-8,27%
Max Jul 2017	23,94%	22,92%	23,35%	22,63%	20,12%	19,17%	18,35%	37,42%	19,52%
Min Jul 2017	-10,50%	-14,80%	-22,36%	-16,22%	-13,19%	-9,07%	-11,71%	-13,73%	-13,17%
Max Aug 2017	12,33%	14,99%	17,92%	14,67%	24,70%	18,18%	42,24%	21,31%	9,79%
Min Aug 2017	-5,46%	-4,04%	-9,74%	-8,53%	-11,26%	-5,75%	-8,50%	-7,48%	-3,51%
Max Sep 2017	15,30%	17,09%	19,98%	27,99%	10,48%	21,08%	20,24%	28,91%	15,70%
Min Sep 2017	-18,74%	-22,81%	-27,98%	-38,92%	-18,23%	-32,64%	-25,41%	-29,73%	-23,23%
Max Out 2017	12,85%	11,38%	94,77%	13,11%	17,31%	18,12%	9,23%	7,70%	4,13%
Min Out 2017	-6,81%	-4,89%	-23,36%	-8,33%	-10,04%	-7,95%	-5,35%	-8,20%	-2,56%
Max Nov 2017	10,24%	15,78%	36,06%	31,25%	17,84%	13,92%	19,19%	13,69%	9,12%
Min Nov 2017	-7,36%	-9,60%	-20,88%	-17,81%	-18,75%	-10,89%	-17,25%	-12,68%	-5,94%
Max Dec 2017	25,25%	26,46%	44,47%	57,71%	83,46%	47,60%	28,18%	170,59%	14,87%
Min Dec 2017	-12,47%	-17,81%	-15,75%	-18,46%	-12,51%	-16,55%	-17,19%	-30,33%	-17,06%
Max Jan 2018	11,73%	14,47%	58,68%	26,19%	25,40%	18,93%	17,62%	54,31%	10,39%
Min Jan 2018	-16,85%	-18,44%	-26,38%	-30,79%	-29,76%	-19,09%	-22,80%	-25,90%	-22,92%
Max Feb 2018	11,48%	13,64%	11,96%	23,44%	18,51%	33,73%	19,27%	29,91%	15,36%
Min Feb 2018	-15,97%	-16,38%	-15,43%	-19,69%	-17,03%	-15,33%	-18,80%	-20,72%	-17,84%
Max Mar2018	8,04%	5,31%	13,47%	7,84%	13,71%	6,31%	9,92%	19,22%	8,70%
Min Mar 2018	-10,06%	-13,51%	-14,30%	-12,71%	-11,51%	-12,96%	-17,84%	-16,73%	-11,50%
Max Apr 2018	13,22%	14,49%	17,09%	14,08%	16,73%	12,71%	16,65%	17,43%	13,31%
Min Apr 2018	-8,78%	-13,10%	-15,27%	-12,19%	-14,36%	-12,68%	-13,14%	-13,42%	-11,31%
Max May 2018	5,50%	13,45%	14,51%	10,09%	8,85%	7,14%	5,73%	7,04%	8,64%
Min May 2018	-6,66%	-9,90%	-11,21%	-10,43%	-9,67%	-8,51%	-11,31%	-11,06%	-9,15%

Max Jun 2018	5,33%	8,85%	9,34%	5,36%	4,97%	7,51%	9,47%	8,31%	6,99%
Min Jun 2018	-9,90%	-11,90%	-12,13%	-11,44%	-10,87%	-12,23%	-10,53%	-12,72%	-12,30%
Max Jul 2018	9,25%	6,85%	17,94%	19,92%	8,41%	8,32%	10,35%	19,19%	7,68%
Min Jul 2018	-6,11%	-8,87%	-10,25%	-11,29%	-6,18%	-5,91%	-10,50%	-9,50%	-7,41%
Max Aug 2018	4,16%	9,61%	10,23%	49,53%	25,41%	11,11%	13,47%	12,55%	12,75%
Min Aug 2018	-6,62%	-10,35%	-12,70%	-9,58%	-12,89%	-8,33%	-12,50%	-12,32%	-9,84%
Max Sep 2018	3,30%	15,28%	17,68%	30,96%	37,96%	9,72%	12,50%	11,89%	8,50%
Min Sep 2018	-7,73%	-18,69%	-10,33%	-20,37%	-14,50%	-13,69%	-16,59%	-17,58%	-13,90%
Max Out 2018	4,86%	7,14%	6,14%	7,18%	10,91%	5,15%	6,14%	6,93%	5,60%
Min Out 2018	-5,00%	-16,07%	-14,32%	-9,94%	-17,15%	-11,64%	-11,53%	-12,60%	-11,47%
Max Nov 2018	11,43%	11,30%	12,33%	8,61%	10,39%	11,46%	11,19%	18,56%	10,65%
Min Nov 2018	-13,37%	-15,75%	-14,90%	-8,51%	-9,10%	-13,44%	-18,91%	-11,96%	-13,40%
Max Dec 2018	10,37%	18,07%	13,94%	19,20%	14,10%	14,92%	18,94%	10,36%	12,38%
Min Dec 2018	-6,45%	-11,59%	-11,99%	-7,38%	-9,90%	-8,71%	-10,21%	-10,31%	-9,26%
Max Jan 2019	6,02%	10,41%	5,79%	4,25%	10,67%	12,48%	9,91%	5,84%	6,76%
Min Jan 2019	-8,83%	-14,70%	-11,23%	-5,91%	-10,30%	-13,13%	-13,68%	-14,45%	-11,86%
Max Feb 2019	7,86%	14,09%	8,74%	6,12%	8,99%	30,82%	11,36%	7,56%	10,20%
Min Feb 2019	-8,02%	-14,45%	-10,64%	-5,23%	-9,38%	-13,54%	-8,92%	-10,19%	-10,27%
Max Mar2019	3,58%	7,87%	11,43%	2,34%	3,74%	14,43%	4,57%	10,35%	6,42%
Min Mar 2019	-2,23%	-3,39%	-4,24%	-1,65%	-2,40%	-4,03%	-3,63%	-6,71%	-3,34%
Max Apr 2019	17,36%	15,60%	11,22%	18,32%	12,41%	25,56%	15,16%	24,55%	15,78%
Min Apr 2019	-4,88%	-6,86%	-7,60%	-10,91%	-6,71%	-9,84%	-9,43%	-9,94%	-7,40%
Max May 2019	12,95%	13,82%	21,24%	11,32%	25,68%	15,61%	13,99%	25,26%	12,11%
Min May 2019	-6,86%	-7,67%	-7,79%	-6,50%	-7,98%	-6,89%	-7,51%	-8,97%	-6,61%
Max Jun 2019	10,95%	8,54%	4,19%	4,84%	7,13%	12,11%	7,66%	8,93%	7,39%
Min Jun 2019	-14,09%	-12,61%	-12,32%	-5,89%	-12,56%	-12,85%	-12,22%	-10,30%	-12,27%
Max Jul 2019	10,74%	7,14%	12,58%	19,76%	4,68%	12,97%	14,09%	16,54%	8,84%
Min Jul 2019	-13,01%	-15,54%	-9,66%	-8,64%	-9,21%	-12,56%	-17,30%	-17,24%	-12,82%
Max Aug 2019	7,62%	5,19%	6,57%	5,07%	6,36%	5,07%	8,64%	4,84%	4,15%
Min Aug 2019	-7,75%	-10,59%	-6,72%	-4,44%	-11,23%	-9,89%	-8,23%	-5,83%	-8,66%
Max Sep 2019	6,03%	5,83%	30,38%	7,38%	10,11%	5,84%	10,08%	10,19%	3,79%
Min Sep 2019	-11,40%	-16,74%	-12,87%	-10,38%	-12,47%	-16,50%	-13,82%	-10,47%	-15,13%
Max Out 2019	15,58%	11,93%	7,95%	5,75%	7,07%	13,72%	10,12%	17,54%	12,30%
Min Out 2019	-6,98%	-5,75%	-4,51%	-7,53%	-6,00%	-7,65%	-6,44%	-7,17%	-6,25%
Max Nov 2019	4,34%	2,71%	10,57%	6,18%	2,95%	5,01%	8,20%	8,72%	3,58%
Min Nov 2019	-4,99%	-8,10%	-5,83%	-5,59%	-5,71%	-8,17%	-7,46%	-6,41%	-9,25%
Max Dec 2019	9,58%	8,56%	4,45%	8,18%	6,80%	9,98%	6,65%	8,25%	8,58%
Min Dec 2019	-4,21%	-8,24%	-9,27%	-4,86%	-11,34%	-8,15%	-9,12%	-8,57%	-7,09%
Max Jan 2020	8,39%	15,07%	11,72%	7,94%	13,30%	17,60%	11,67%	12,95%	18,57%
Min Jan 2020	-3,16%	-4,79%	-4,64%	-5,75%	-4,24%	-6,38%	-3,89%	-8,59%	-4,98%
Max Feb 2020	4,71%	12,53%	8,54%	14,08%	8,68%	6,29%	8,62%	22,92%	6,27%
Min Feb 2020	-5,58%	-8,93%	-9,23%	-7,61%	-8,88%	-14,29%	-9,19%	-10,51%	-8,31%
Max Mar2020	18,19%	18,94%	18,21%	13,22%	15,30%	21,05%	15,13%	17,64%	18,08%
Min Mar 2020	-37,17%	-42,35%	-33,64%	-29,62%	-32,92%	-36,17%	-38,99%	-26,48%	-38,40%
Max Apr 2020	12,73%	17,83%	13,75%	12,46%	8,97%	9,15%	9,14%	7,60%	9,74%

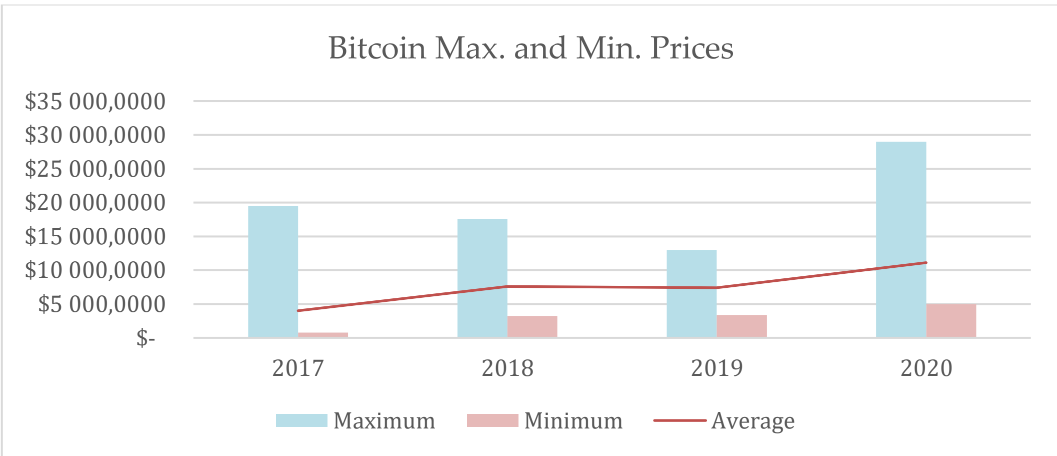
Min Apr 2020	-5,98%	-7,26%	-8,17%	-3,69%	-6,42%	-8,86%	-8,34%	-6,01%	-7,37%
Max May 2020	7,37%	9,82%	11,34%	5,34%	3,98%	6,47%	10,27%	4,67%	5,38%
Min May 2020	-8,73%	-10,87%	-10,63%	-5,89%	-8,62%	-10,37%	-6,93%	-8,95%	-9,06%
Max Jun 2020	7,46%	6,93%	6,92%	3,60%	3,60%	5,57%	3,95%	9,41%	6,20%
Min Jun 2020	-6,27%	-6,36%	-9,12%	-5,11%	-6,26%	-6,79%	-8,23%	-10,78%	-7,17%
Max Jul 2020	10,96%	8,90%	16,01%	53,72%	10,77%	10,46%	6,10%	19,14%	5,66%
Min Jul 2020	-1,59%	-2,00%	-5,21%	-20,06%	-2,07%	-2,87%	-4,77%	-5,27%	-2,26%
Max Aug 2020	4,83%	11,47%	10,39%	14,39%	11,82%	9,50%	10,99%	33,95%	6,71%
Min Aug 2020	-6,00%	-6,56%	-6,34%	-9,57%	-4,68%	-7,59%	-8,63%	-10,74%	-5,50%
Max Sep 2020	5,02%	9,65%	5,81%	3,46%	5,29%	5,95%	7,77%	21,06%	6,54%
Min Sep 2020	-10,24%	-13,65%	-14,25%	-10,25%	-10,81%	-17,78%	-14,38%	-19,13%	-12,89%
Max Out 2020	7,61%	6,24%	7,17%	2,20%	6,35%	12,75%	8,70%	4,55%	5,60%
Min Out 2020	-2,80%	-3,80%	-5,09%	-3,06%	-2,77%	-3,64%	-7,43%	-5,75%	-3,37%
Max Nov 2020	10,23%	9,82%	49,69%	17,53%	39,68%	14,53%	8,10%	23,72%	8,56%
Min Nov 2020	-8,44%	-9,09%	-14,19%	-12,80%	-16,13%	-13,45%	-7,59%	-13,17%	-10,74%
Max Dec 2020	9,75%	7,94%	26,17%	21,28%	30,63%	13,99%	6,77%	27,03%	8,56%
Min Dec 2020	-4,54%	-8,06%	-22,01%	-16,42%	-42,33%	-10,43%	-6,36%	-15,86%	-9,97%

Table 13: Maximum and Minimum monthly returns. Source: https://coinmarketcap.com

Graphs

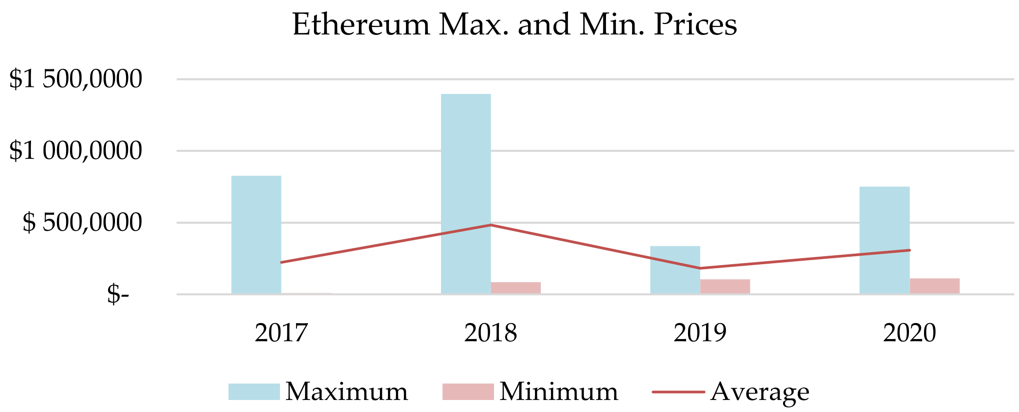
Graph 3: BTC daily closing prices. Source: https://coinmarketcap.com

Graph 4: BTC maximum and minimum prices per year. Source: https://coinmarketcap.com



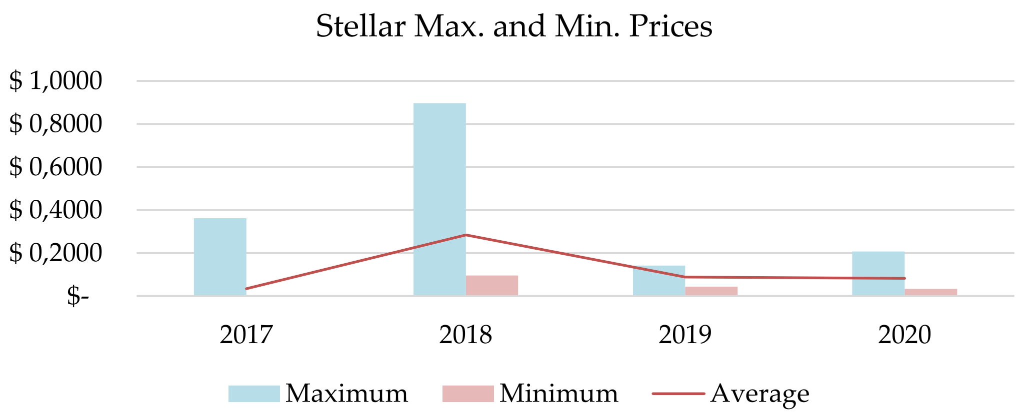
Graph 5: ETH daily closing prices. Source: https://coinmarketcap.com

Graph 6: ETH maximum and minimum prices per year. Source: https://coinmarketcap.com

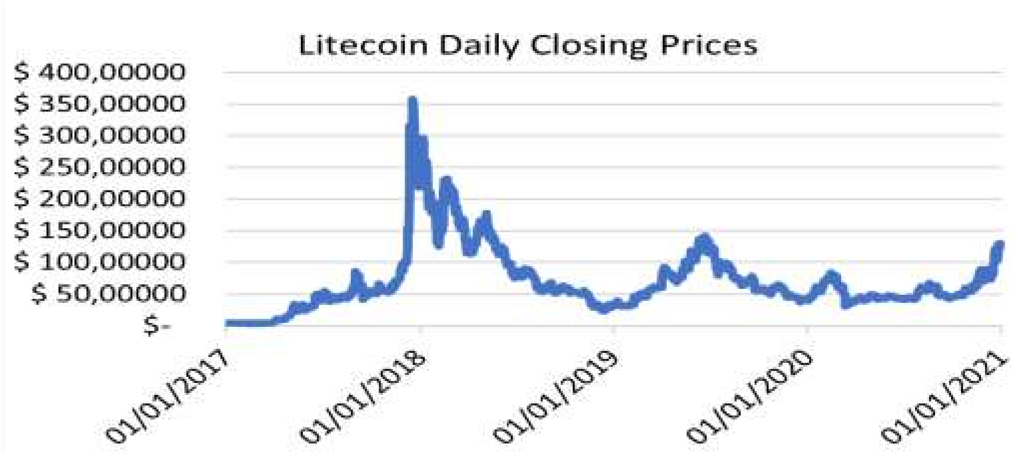


Graph 7: XLM daily closing prices. Source: https://coinmarketcap.com

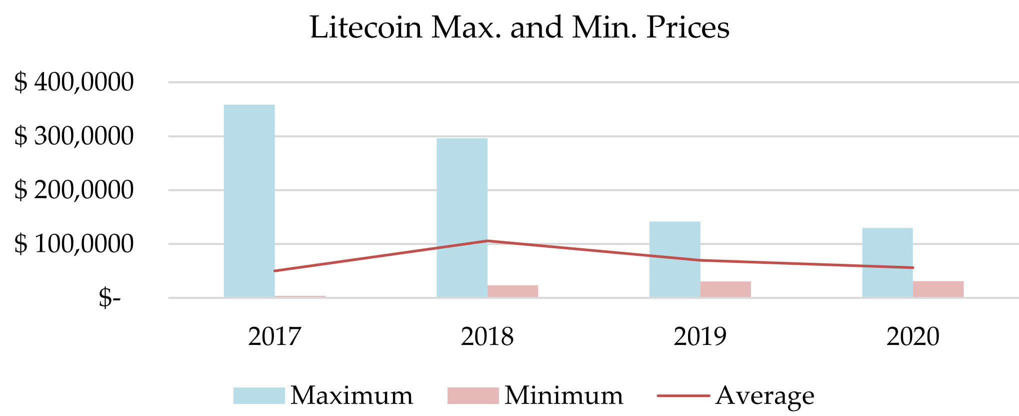
Graph 8: XLM maximum and minimum prices per year. Source: https://coinmarketcap.com



Graph 9: LTC daily closing prices. Source: https://coinmarketcap.com

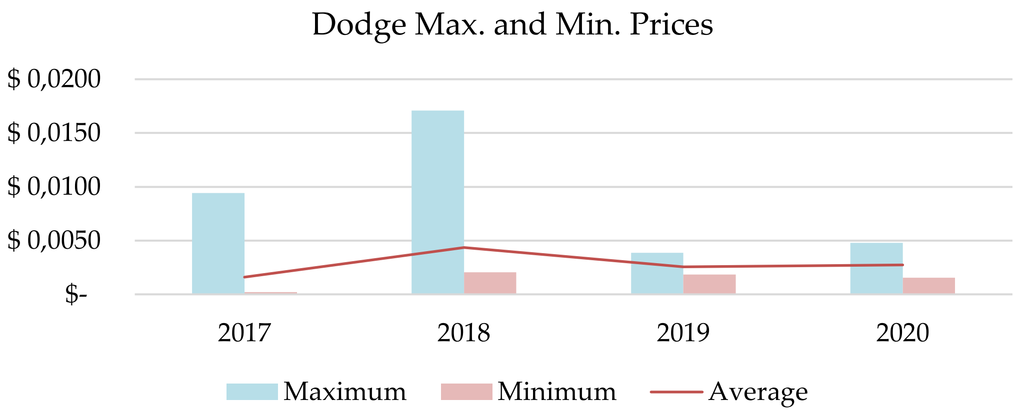


Graph 10: LTC maximum and minimum prices per year. Source: https://coinmarketcap.com



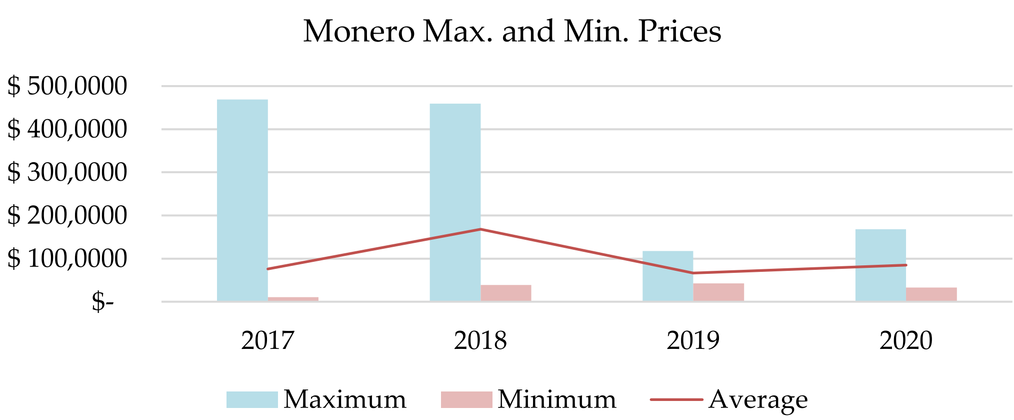
Graph 11: DOGE maximum and minimum prices. Source: https://coinmarketcap.com

Graph 12: DOGE maximum and minimum prices per year. Source: https://coinmarketcap.com



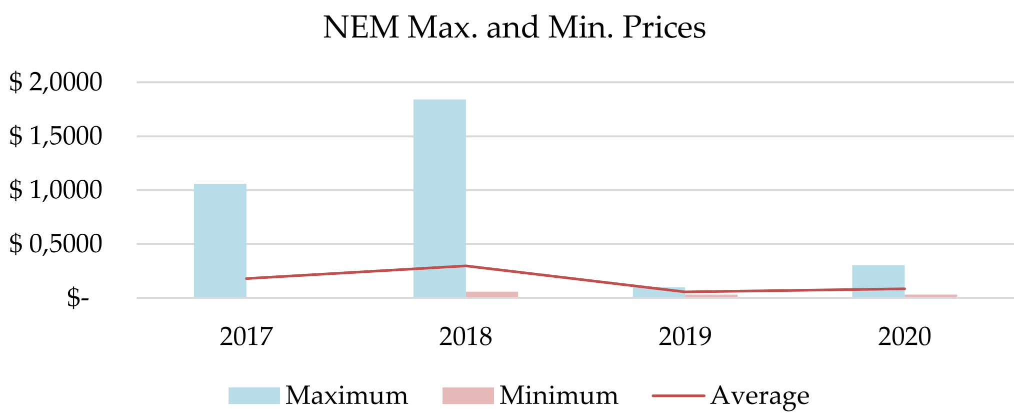
Graph 13: XMR daily closing prices. Source: https://coinmarketcap.com

Graph 14: XMR maximum and minimum prices per year. Source: https://coinmarketcap.com



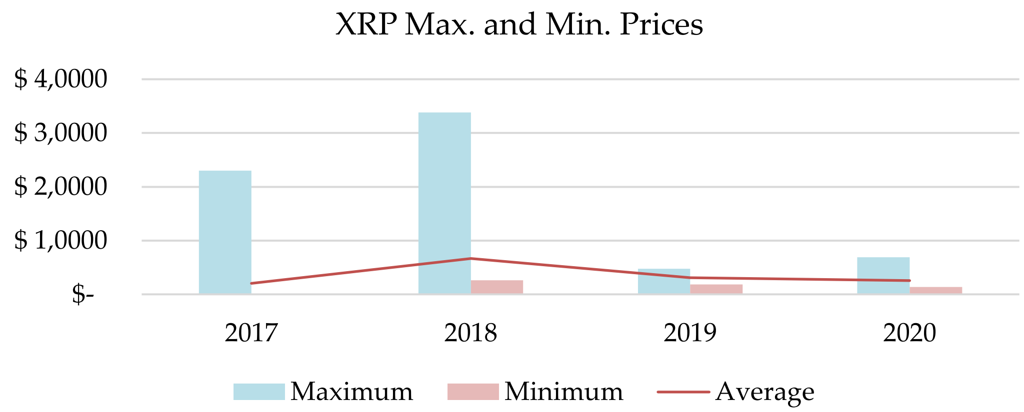
Graph 15: XEM maximum and minimum prices per year. Source: https://coinmarketcap.com

Graph 16: XEM maximum and minimum prices per year. Source: https://coinmarketcap.com



Graph 17: XRP daily closing prices. Source: https://coinmarketcap.com

Graph 18: XRP maximum and minimum prices per year. Source: https://coinmarketcap.com



Graph 19: CCi30 maximum and minimum prices per year. Source: https://cci30.com

Graph 20: CCi30 maximum and minimum prices per year. Source: https://cci30.com