UNIVERSIDADE CATÓLICA PORTUGUESA

Herding Behavior in the Cryptocurrency Market

The Impact of COVID-19

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Resumo

Esta tese investiga o “herding behavior” no mercado de criptomoedas durante 2017-2022, com foco no impacto da pandemia COVID-19. Utilizando um modelo quantitativo, dados das oito principais criptomoedas e o índice CCi30, o estudo procurou determinar se a pandemia intensificou o herding behavior entre os investidores. Contrariamente ao esperado, a pesquisa concluiu que não houve herding no período pré-pandemia nem durante a pandemia. Esta conclusão desafia alguma literatura sobre o comportamento dos investidores em tempos de crise, sugerindo que os investidores do mercado de criptomoedas aparentam confiar mais em análises e estratégias individuais do que em movimentos coletivos do mercado. Assim, os resultados desta pesquisa contrastam com as conclusões predominantes de estudos anteriores sobre herding. Esta percepção adiciona uma dimensão significativa ao entendimento da psicologia do mercado, especialmente em contextos de circunstâncias extraordinárias, fornecendo informações importantes para a implantação de políticas,, para os investidores e para a comunidade financeira mais ampla.

Palavras-chave: Criptomoedas, Herding Behavior, COVID-19, Finanças Comportamentais, Psicologia do Investidor.

Abstract

This thesis delves into the phenomenon of herding behavior within the cryptocurrency market from 2017 to 2022, with a particular emphasis on the COVID-19 pandemic's influence. Utilizing a quantitative approach and analyzing data from eight leading cryptocurrencies and the CCi30 index, the study sought to determine if the pandemic led to an increase in herding behavior among investors. Contrary to expectations, the research concluded that herding behavior was not prevalent in the period before the pandemic nor during the pandemic itself. This conclusion challenges existing assumptions about investor behavior in times of crisis, suggesting that cryptocurrency market's investors may rely more on individual analysis and strategies than on collective market movements. Therefore, the findings of this research stand in contrast to the prevailing conclusions drawn from previous studies, highlighting the nuanced nature of investor sentiment and decision-making within the cryptocurrency market. This insight adds a significant dimension to the understanding of market psychology, especially under extraordinary circumstances, providing valuable information for policymakers, investors, and the broader finance community.

Keywords: Cryptocurrency, Herding Behavior, COVID-19, Behavioral Finance, Investor Psychology.

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Chapter 1 Introduction

1.1 General Background

The Efficient Market Hypothesis (EMH), introduced by E. F. Fama (1970) suggests that financial markets are efficient, with asset prices incorporating all available information. However, challenges in explaining events like financial crises have prompted exploration of alternative theories (Sharma & Kumar, 2019). Behavioral Finance, addressing EMH limitations, focuses on human behavior in financial decision-making, challenging the notion of purely rational investors and introducing psychological biases (Mullainathan & Thaler, 2000; Shefrin & Statman, 2012).

Within Behavioral Finance, herding behavior has gained significant attention, as it concerns the conduct of investors imitating others' trading decisions despite private information (Bikhchandani et al., 1992; Chauhan et al., 2017). Herding is associated with market anomalies, increased volatility, and asset price deviations (Javaira & Hassan, 2015; Shiller, 1999). The cryptocurrency market's volatility and unique psychological aspects offer insights into how traditional finance theories may need adaptation (Bikhchandani & Sharma, 2000; Bui et al., 2018).

The cryptocurrency market has experienced remarkable growth, with global market capitalization soaring from 15 billion USD in 2017 to 1.8 trillion USD by November 2023, according to Statistica.com (de Best, 2024a). This growth coincided with a surge in the number of cryptocurrencies from over 1,000 in 2017 to over 9,000 in 2023, alongside approximately 420 million cryptocurrency users globally (de Best, 2024b). Despite this expansion, the market is prone to speculation, bubbles, and crashes due to investor behavior, often influenced by herding tendencies (Bouoiyour & Selmi, 2014; Bukovina & Marticek, 2016; Dwyer, 2015; Dyhrberg, 2016). High volatility and regulatory uncertainties further contribute to its unpredictability and risks (Ciaian et al., 2016). Bitcoin remains dominant within the market (Gkillas & Katsiampa, 2018), despite issues like fraud and security threats continuing to undermine investor confidence (Moore & Christin, 2013). Additionally, the COVID-19 pandemic presented unique challenges and opportunities for studying herding behavior in this context.

1.2 Research Gaps

The exploration of herding behavior in financial markets has yielded varied conclusions, leading to a dispersion of findings, and leaving certain gaps in the understanding of this phenomenon. While some studies assert that herding is more prevalent in extreme market conditions (Christie & Huang, 1995; Zhou & Lai, 2009), others argue that herding is independent of these conditions (Hwang & Salmon, 2004). This topic remains a significant research gap in the field as the conflicting nature of these conclusions raises the empirical question of whether herding is truly dependent on market conditions (Chang et al., 2000).

While empirical studies have frequently examined herding behavior in financial markets (Economou et al., 2011; Yao et al., 2014), this phenomenon has not been thoroughly investigated in the cryptocurrency market. Only a few studies have approached the market from a behavioral perspective, and the existing research remains superficial (Nadarajah & Chu, 2017). Cryptocurrencies commonly demonstrate remarkable returns and significant volatility, often lacking clear justifying factors. The cryptocurrency market is marked by a deficient legal framework and a shortage of reliable information, where inexperienced investors, relying on limited information, frequently enter the market without a comprehensive understanding of the associated risks (Bouri et al., 2019). Consequently, there is a need for further research that explore behavioral concepts and human decision-making to better explain the mechanics of herding behavior in the cryptocurrency market.

Furthermore, the intersection of the cryptocurrency market and the COVID-19 pandemic introduces another layer of complexity. While the impact of COVID-19 on traditional financial markets has been extensively studied, the cryptocurrency market has received comparatively less attention (Youssef & Waked, 2022). Despite the existence of some studies of how the COVID-19 pandemic has also affected the cryptocurrency market efficiency (Ali et al., 2020; Montasser et al., 2022; Wang & Wang, 2021; Youssef & Waked, 2022), there is still a need to understand how herding behavior in the cryptocurrency market is influenced by the uncertainties and extreme conditions introduced by the COVID-19 crisis. This gap suggests an opportunity for future studies to explore the connection of herding behavior, cryptocurrency markets, and the unique challenges posed by the pandemic.

1.3 Research Question

The goal of this investigation is to answer the following questions:

Q1: "Is herding behavior present in the Cryptocurrency market during the period of 2017 to 2019?"

The first proposed research question is to explore whether herding behavior, characterized by investors imitating the trading decisions of others, is indeed present in the cryptocurrency market for the period before the COVID-19 pandemic, hence 2017 until 2019. Given that the cryptocurrency market is marked by a deficient legal framework and a shortage of reliable information, investors frequently enter the market without a comprehensive understanding of the associated risks (Bouri et al., 2019). Therefore, the analysis of such phenomenon is relevant as cryptocurrencies commonly demonstrate remarkable returns and significant volatility, often lacking clear justifying factors (Kaiser & Stöckl, 2020)

Q2: "Does the COVID-19 pandemic increased (or decreased) investors' herding behavior in the cryptocurrency market?".

Based on Q1 and acknowledging that, due to its nature, the cryptocurrency market has been prone to high volatility in the past few years (Youssef & Waked, 2022), the second proposed research question will investigate the specific impact of the COVID-19 pandemic on herding behavior within this market for the period of 2020 until 2022. Often investors are influenced by others regardless of their own analysis, which points to potential herding behavior, possibly intensified by uncertainty and extreme market conditions (Ali et al., 2020; Montasser et al., 2022; Wang & Wang, 2021; Youssef & Waked, 2022). Therefore, the second goal of the present study is to understand if the pandemic in fact increased (or decreased) the levels of herding in the cryptocurrency market during the COVID-19 pandemic.

1.4 Originality

Originality in terms of this dissertation comes from the following facts: firstly, this research uses the diversified sample of 8 of the major capitalized cryptocurrencies and uses the CCi30 index to capture the overall growth of the cryptocurrency sector. Contrasting with other studies that use smaller or broader samples without encompassing for a market index (Ajaz & Kumar, 2018; Bouri et al., 2019; Jalal et al., 2020). Secondly, this research explores herding behavior among cryptocurrency investors using more recent data (Susana et al., 2020; Yarovaya et al., 2021), extending the analysis to pandemic years, ranging from years 2017 until 2022.

Lastly, few studies have specifically examined herding behavior in the cryptocurrency market during the COVID-19 pandemic (Bouri et al., 2019; Kaiser & Stöckl, 2020; Vidal-Tomás et al., 2019). This paper distinguishes itself from existing literature (Ajaz & Kumar, 2018; Conlon & McGee, 2020; Rubbaniy et al., 2021; Susana et al., 2020; Youssef & Waked, 2022) by focusing on a targeted sample size consisting of the eight most capitalized cryptocurrencies established before August 2017, along with the market index CCi30. This approach ensures a homogeneous sample for a robust analysis, offering insights into the behavior of influential players in the cryptocurrency market during the pandemic period.

1.5 Contribution to knowledge

This study contributes to the behavioral finance discourse on cryptocurrency market investment, specifically through an empirical analysis of herding behavior. Therefore, this thesis is another empirical study on the subject that aims to explain the investors' behavior in the cryptocurrency market. It enriches the academic understanding by providing insights into how major market disruptions, like the pandemic, influence investor psychology and decision-making processes.

Additionally, this dissertation may appeal to the following stakeholders: policymakers and regulators, unexperienced traders, and individual and institutional investors. Policymakers and regulators can expect a better understanding of the cryptocurrency market in order to create new regulations aiming to a more stable and robust financial system infrastructure to traders. Unexperienced traders, who increasingly register their presence in the cryptocurrency market, can expect to improve trading strategies that consider herding. Finally, to individual and institutional investors, this research can create a greater understanding of the price formation and risk structure of cryptocurrencies, which could also impact the portfolio risk management when considering cryptocurrencies as an alternative investment.

1.6 Outline of the following chapters

The remaining chapters of this thesis are organized as follows: Chapter 2 will report the available literature on the topic including a review on market efficiency (EMH), behavioral finance and herding; Chapter 3 will present the methodology and data used for this study; Chapter 4 will describe the empirical results and the discussion; Lasty, Chapter 5 will present the conclusions achieved with this study.

Chapter 2 Literature Review

2.1 Herding

Herding behavior in finance is a phenomenon rooted in behavioral economics and has been a subject of extensive research and analysis. This investment behavior creates a huge volatility in prices, as it takes the price of an asset away from its fundamental value (Kumar, 2020). Authors Hwang & Salmon (2004)describe herding as investors abandoning their information and beliefs to follow peers rather than market trends. This behavior can distort individual asset risk-return relationships but is considered rational as it can occur even when investors act reasonably individually. In the same way, Bikhchandani & Sharma (2000) describe that investors engage in herding behavior when they imitate others by being influenced by their actions. This occurs when an investor refrains from making an investment independently, upon learning others have decided against it. Thus, investors collectively engage in herding on investment choices that may be suboptimal for all involved.

In summary, Kumar (2020) emphasizes on the impact of herding on asset's price volatility and their deviation from their fundamental value, while Hwang & Salmon (2004) focus on the ignoring personal information seeking peer imitation, viewing it as rational. Bikhchandani & Sharma (2000) explore the psychological aspect, highlighting how awareness of others' decisions triggers herding, influencing suboptimal investments. These perspectives offer a comprehensive view, depicting herding as a multifaceted phenomenon influenced by group dynamics, rationality, and psychology.

Despite the difficulty of clearly highlighting all the concepts of herding as they complement each other, Kumar's general description will be followed in this thesis in order to investigate the patterns of investors' behaviors given the effects on prices and volatility of the cryptocurrencies. Knowing that cryptocurrencies are highly volatile, Kumar's approach directly ties herding behavior to observable market phenomena, such as price volatility and deviations from intrinsic values.

2.2 Main theories

2.2.1 Efficient Market Hypothesis (EMH) Theory

The Efficient Markets Hypothesis (EMH) suggests that stock markets are efficient, and investors make rational decisions. It relies on the assumption of *Homo Economicus*, where market participants are rational decision-makers seeking to maximize utility (Simon, 1955). Rationality is crucial to EMH, implying accurate information processing and rational decision-making (Kahneman & Tversky, 1979). EMH is associated with the "random walk" idea, where stock prices are unpredictable based on past information, and new information is quickly incorporated (Samuelson, 1965). This randomness means future price movements cannot be predicted from past prices, leading to no consistent above-average returns (E. Fama, 1965).

Fama described three forms of the Efficient Market Hypothesis each with different assumptions about the availability and speed of information in the market: the weak form, semi-strong form, and strong form. In the weak form of efficiency, it is posited that all historical price and volume information is already reflected in the current stock prices. In the semi-strong form of efficiency, not only historical information but also all publicly available information, including both historical and public financial statements, is already incorporated into stock prices. Lastly, the strong form of market efficiency asserts that all information, whether public or private, is fully reflected in current stock prices. (E. Fama, 1965; E. F. Fama, 1970; Timmermann & Granger, 2004). Therefore, fundamental analysis may only be useful under the weak form of EMH, as it suggests that only past price and volume information is reflected in stock prices. However, in both semi-strong and strong forms, it becomes ineffective as all public and private information is already priced in. Similarly, technical analysis is considered ineffective across all three forms of EMH for guiding investor decisions.

On the other hand, critics argue that the Efficient Markets Hypothesis (EMH) fails to explain anomalies and profitability in stock markets, challenging its assertion that markets quickly integrate all available information (Shiller, 2003). Market bubbles and crashes are cited as evidence against EMH, suggesting it does not predict extreme movements (Brock, 2011). These criticisms highlight the need for a nuanced understanding of financial markets. Additionally, influential studies questioned investor rationality and supported behavioral finance as a better theory of asset pricing gaining momentum in explaining stock returns (Shiller, 2003; Shleifer, 2000).

2.2.2 Behavioral Finance

Behavioral finance, as an alternative theory, accounts for the irrational nature of human behavior and decision-making in markets. Prominent researchers have supported behavioral finance, establishing it as a widely accepted alternative theory of asset pricing (Akerlof, 2002; Camerer, 1999; Fudenberg, 2006; Tomer & F., 2007), despite still not being a credible alternative to EMH.

Nevertheless, numerous researchers have explored its possibilities and strengths in explaining stock returns, and the field is currently expanding.

The real behavior of individuals and organizations reveals the inaccuracy of the traditional economic models, as decisions, even well-thought-out ones, are prone to errors or biases (Mullainathan & Thaler, 2000; De Grauwe & Macchiarelli, 2015; Gomes, 2023). Therefore, behavioral finance provides a more realistic and nuanced understanding of financial markets than the idealized assumptions of the EMH. In examining the practical implications of behavioral finance, numerous examples of market anomalies, biases, and heuristics emerge, offering valuable insights into the complexities of financial decision-making (Barberis & Thaler, 2003). Heuristics are mental shortcuts or rule of thumb that simplifies decision-making processes in financial contexts. While efficient, these heuristics can lead to biases and errors in judgment, impacting investor behavior and market outcomes.

This thesis is focusing in one of these biases, namely herding behavior. However, as described below in Table 1, there are several biases influencing investor behavior in financial markets. Understanding these psychological factors is crucial for interpreting market dynamics and improving investment strategies.

Biases	Concept
Overconfidence	Investors tend to overestimate their own abilities and information, leading them to believe that their forecasts and investment decisions are more accurate than they actually are. This bias can result in excessive trading and unwarranted risk-taking.
Confirmation	Individuals have a natural inclination to seek out information that confirms their existing beliefs and to ignore information that contradicts those beliefs. In finance, this bias can lead investors to selectively consider data that supports their investment decisions while neglecting contradictory evidence.
Loss Aversion	Refers to the tendency of individuals to prefer avoiding losses rather than acquiring equivalent gains. Investors may be more averse to losses than motivated by potential gains, leading to risk-averse behavior and suboptimal investment decisions.
Anchoring	Anchoring occurs when individuals rely too heavily on the first piece of information they receive (the "anchor") when making decisions. In finance, investors may be influenced by initial stock prices or other reference points, impacting their subsequent valuation and decision-making processes.
Regret Aversion	Investors may make decisions to avoid the feeling of regret, even if those decisions are not optimal from a financial perspective. This bias can result in suboptimal investment choices, as individuals may avoid actions that could lead to regret, such as realizing losses.
Framing Effect	The framing effect occurs when the way information is presented influences decision-making. In finance, the same information presented in different ways can lead to different investment choices.
Recency	Investors may give more weight to recent events and trends when making decisions, assuming that current market conditions will persist. This bias can contribute to market bubbles and abrupt market corrections as investors extrapolate recent trends into the future.
Hindsight	Hindsight bias involves the tendency to see events as having been predictable after they have already occurred. Investors may incorrectly believe they could have foreseen market movements after the fact, leading to overconfidence and potentially risky decision-making.

Table 1: Common Biases in Behavioral Finance.

Self-elaboration. Sources: (Barberis & Thaler, 2003; Kahneman & Tversky, 1979; Lakonishok et al., 1992; Mullainathan & Thaler, 2000; Shefrin & Statman, 2012)

Behavioral economics provides a nuanced view of individuals as complex agents influenced by cognitive constraints, emotions, and social context

(Mullainathan & Thaler, 2000). This shift acknowledges human imperfection and considers decision-making in multidimensional terms. While valuable, behavioral economics faces challenges in accurately predicting individual behavior due to cognitive biases and situational factors. Additionally, it may introduce subjectivity into financial analysis and lacks clear investment guidelines. Despite limitations, behavioral economics enriches understanding of financial markets and investor behavior, becoming a crucial research program (Shiller, 2003) that contrasts with EMH.

2.2.3 Herding Behavior

In finance, "herding behavior" describes individuals or investors following the crowd rather than making independent decisions. Researchers have focused on studying herding due to its significant impact on price deviations from intrinsic value. Studies in stock markets often examine herding behavior during exceptional market conditions like crises, bullish or bearish markets, high or low volatility, and trading volume (Economou et al., 2011; Raimundo Júnior et al., 2022).

In the literature, herding behavior is categorized into rational and irrational forms. Rational herding involves informed decision-making, where individuals follow others based on perceived information. Irrational herding, however, entails following the crowd without clear reasons (Bikhchandani & Sharma, 2000). Rational herding can be further classified into spurious and intentional types. Spurious herding occurs due to shared characteristics among investors, while intentional herding involves investors ignoring their own information to follow others for reputational reasons or a belief in their superior knowledge

(Devenow & Welch, 1996; Guo et al., 2020; Teh & Bondt, 1997; Voronkova & Bohl, 2005). See Figure 1 below:

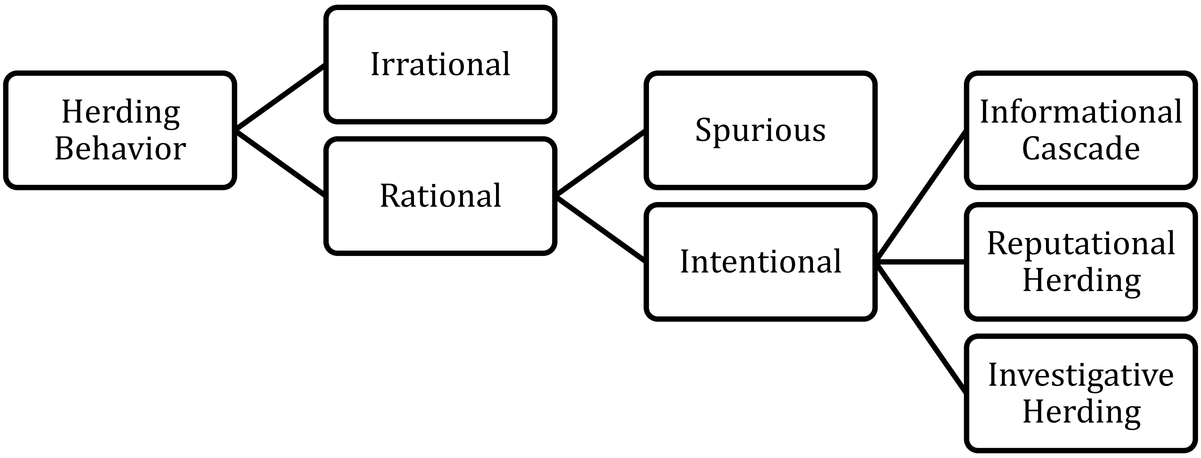

Figure 1: Classification of Herding Behavior
Self-Elaboration

Understanding investor herding and its contributing factors is crucial for developing policies to mitigate its impact on financial market stability. This is particularly significant in the case of intentional herding, often marked by fragility and idiosyncrasy, due to its potential to result in excessive volatility and systemic risk (Shiller, 1999).

As stated in Figure 1, within the intentional herding category, herding can yet be classified as informational cascades, reputational herding, and investigative herding (Devenow & Welch, 1996; Graham, 1999). Informational cascades in herding occur when individuals choose to disregard their private information, opting instead to mimic the actions of those who acted earlier. This phenomenon is particularly pronounced when the aggregate information becomes so overwhelming that an individual's singular piece of private information is insufficient to sway the decision of the crowd (Banerjee, 1992; Bikhchandani et al., 1992). Such cascading behavior may result in market irregularities, giving rise to unfounded trends, booms, and crashes, contributing to inefficiencies in financial markets (Graham, 1999).

Reputational herding shares similarities with informational cascades, as individuals also choose to ignore private information in favor of mimicking the actions of previous agents. However, in reputational herding models, an additional layer of mimicking emerges due to positive reputational externalities and investor choose to imitate another investor or group of investors, yielding reputational benefits (Huddart, n.d.; Scharfstein & Stein, 1990; Trueman, 1994).

Investigative herding unfolds when analysts choose to explore information that they anticipate others will also examine. In this scenario, analysts aim to be the first to discover valuable information but can only profit if other investors follow suit and contribute to the anticipated direction of the asset price (Brennan & Hughes, 1991; Dow & Gorton, 1994; Froot et al., 1990; Hirshleifer et al., 1994).

While each type represents a distinct strategy, they are interconnected in their reliance on social influence and the tendency to prioritize collective action over individual information. Informational cascades and reputational herding both involve individuals disregarding their private information in favor of following the actions of others, whether due to the perceived wisdom of the crowd or the desire for reputational benefits. Investigative herding, on the other hand, reflects a proactive approach where analysts anticipate the behavior of others and seek to be first to discover valuable information.

In conclusion, the exploration of intentional herding uncovers its complex forms, with each type reflecting distinct strategies. Overall, herding behavior in financial markets is a critical phenomenon encompassing various motivations and decision-making processes, from rational, informed choices to instinctive, crowd-following actions.

2.3 Empirical evidence

2.3.1 General Herding

Studies have explored investors' herding behavior during market turmoil, finding evidence in European and developed stock markets during crises like the global financial crisis (GFC) and the Eurozone crisis (BenSaïda, 2017; Economou et al., 2011; Litimi et al., 2016; Mobarek et al., 2014). Moreover, herding was observed in US industries during periods of panic (BenMabrouk & Litimi, 2018), and in energy stock prices during extreme downturns, though not consistently during the COVID-19 crisis (Chang et al., 2000; Espinosa-Méndez & Arias, 2021; Kizys et al., 2021). The COVID-19 pandemic increased market volatility and elicited a negative response, with varied impacts across global markets (Albulescu, 2021; Ashraf, 2020; Shehzad et al., 2020). These studies indicate that herding behavior intensifies during significant market downturns, with its significance evident in observable market trends such as increased volatility or consistent negative responses to external shocks (Bikhchandani & Sharma, 2000; Cipriani & Guarino, 2008).

2.3.2 Herding in the cryptocurrency market

In the existing literature, there is conflicting evidence regarding the existence of herd behavior in the cryptocurrency market. Notably, in the mainstream discourse on behavioral biases in cryptocurrencies, Bouri et al. (2019) stand out as pioneers in investigating herding within the cryptocurrency market, followed by many others after that. Reflected in Table 2 below, there is a detailed description of the most relevant studies, 12 in total, regarding herding on cryptocurrency market.

In summary, all the studies have in common the use of daily closing prices in US dollars (USD), differing on the subject of analysis, with some studies focusing on a small sample of the 15 most capitalized cryptocurrencies (Ballis & Drakos, 2020; Bouri et al., 2019; Coskun et al., 2020; Kaiser & Stöckl, 2020; Mandaci & Cagli, 2022), some even focusing on just Bitcoin, as the major cryptocurrency, (Haryanto et al., 2020), and others studies examining to up to 100 cryptocurrencies (da Gama Silva et al., 2019; Kaiser & Stöckl, 2020; Kumar, 2020; Raimundo Júnior et al., 2022; Rubbaniy et al., 2021; Vidal-Tomás et al., 2019; Youssef & Waked, 2022).

In the case of empirical study of herding behavior in the cryptocurrency market, researchers commonly employ methodologies proposed by Christie & Huang, (1995) or Chang et al. (2000), specifically the Cross-Sectional Standard Deviation (CSSD) and the Cross-Sectional Absolute Deviation (CSAD). While CSSD and CSAD serve as the primary methodologies in many studies, some researchers combine these approaches with additional methods to enhance their analysis. These supplementary methodologies include the dynamic model proposed by Stavroyiannis & Babalos (2017), the beta-herding state-space model, and other statistical models such as OLS, GARCH, Granger causality, and the cryptocurrency fear index. This variety of methodologies reflects an effort to provide a more comprehensive understanding of herding behavior in this market by means of a multi-dimensional approach (refer to Table 2 below for more details).

Among literature, there is mixed evidence regarding the presence of herd behavior in the cryptocurrency market. The majority of the empirical evidence gathered, corresponding to almost 67% of the studied literature, found robust evidence of herding in the cryptocurrency market across various methods, considering either or both the bearish and bullish moments and periods of high market volatility (Ballis & Drakos, 2020; Haryanto et al., 2020; Kaiser & Stöckl, 2020; Mandaci & Cagli, 2022; Raimundo Júnior et al., 2022; Rubbaniy et al., 2021; Vidal-Tomás et al., 2019; Youssef & Waked, 2022). Additionally, the sample periods encompass a wide temporal range, from 2011 to 2021, indicating a comprehensive examination of herding behavior over time. While the studies primarily focus on USD-denominated cryptocurrencies, they collectively contribute to a deeper understanding of herding dynamics, its impact on market volatility, and the role of external factors such as media coverage and market stress.

On the other hand, almost 17% of the literature, found weak or no evidence of herding effect or even anti-herding behavior in the models studied given the methodology applied (Coskun et al., 2020; da Gama Silva et al., 2019). Despite differences in methodologies, both studies report findings of anti-herding behavior in the cryptocurrency market from 2015 to 2018. Specifically, da Gama Silva et al. (2019) reported weak herding effects during bearish markets but note anti-herding behavior based on the state-space model. Similarly, Coskun et al. (2020) find evidence of anti-herding behavior in each of the models employed, indicating no significant asymmetric behavior during market periods. Notably, both studies focused on USD-denominated cryptocurrencies and utilized daily closing price data for analysis.

In between these findings, another 17% of the literature, found mixed evidence within the same period, where no herding was found in the static model whilst strong evidence of herding was found when employing a more dynamic model (Bouri et al., 2019). Additionally, the studies found that herding was pronounced only when the market was experiencing stress and high volatility. In contrast, anti-herding behavior was found in less volatile or bullish market (Kumar, 2020).

Despite the existence of many studies examining herding in stock and commodity markets, only a few studies focus on the cryptocurrency market, especially over COVID-19. Among the literature, there is strong empirical evidence of the existence of herding behavior during the COVID-19 pandemic period, as investors in the cryptocurrency market tend to follow the crowd when market presents signs of stress and high volatility (Mandaci & Cagli, 2022; Raimundo Júnior et al., 2022; Rubbaniy et al., 2021; Youssef & Waked, 2022).

Study	Author(s)	Period	Sample	Methodology	Evidence/Results
Herding behaviour in cryptocurrencies.	Bouri et al. (2019)	2011-2012	14 of the most capitalized cryptocurrencies	CSAD by Chang et al. (2000) and dynamic model proposed by Stavroyiannis & Babalos (2017).	Lack of evidence supporting herding in the static model. However, their findings indicate evidence in favor of time-varying herding when employing the dynamic model.
Cryptocurrencies : Herding and the transfer currency.	Kaiser & Stöckl (2020)	2015-2019	14 of the most capitalized cryptocurrencies	CSAD by Chang et al. (2000) and the beta-herding state-space model by Hwang & Salmon (2004).	Robust evidence supporting herding behavior in the cryptocurrency market across various methods and weighting schemes.
Herding in the cryptocurrency market: CSSD and CSAD approaches.	Vidal-Tomás et al. (2019)	2015-2017	65 of the most capitalized cryptocurrencies	CSSD by Christie and Huang (1995) and CSAD by Chang et al. (2000)	Observed a significant herding effect during bearish market conditions, noting that smaller cryptocurrencies tended to herd with larger ones.
Herding behavior and contagion in the cryptocurrency market.	da Gama Silva et al. (2019)	2015-2018	50 of the most capitalized cryptocurrencies	CSSD by Christie and Huang (1995), CSAD by Chang et al. (2000) and Hwang and Salmon (2004)	Reported a weak herding effect during bearish markets according to methodologies. However, their results indicated anti-herding behavior based on the state-space model of Hwang and Salmon (2004).
Testing for herding in the cryptocurrency market.	Ballis and Drakos (2020)	2015-2018	6 of the most capitalized cryptocurrencies	CSSD by Christie and Huang (1995)	Found evidence of herding with empirical results providing evidence that the up-events market dispersion follows market movements at a faster pace compared to the down events.
Uncertainty and herding behavior: evidence from cryptocurrencies.	Coskun et al. (2020)	2017-2018	14 of the most capitalized cryptocurrencies	CSAD by Chang et al. (2000), Ordinary Least Squares (OLS), generalized autoregressive conditional heteroscedasticity (GARCH) methods and Time-Varying Markov-Switching (TV-MS) model for both overall sample and sub-periods	The results for the overall sample refer to an anti-herding behavior in each model, suggesting that there was no significant asymmetric behavior during the "up and down" market periods.
Disposition effect and herding behavior in the cryptocurrency market.	Haryanto et al. (2020)	2011-2013	Bitcoin only	CSSD by Christie and Huang (1995) and CSAD by Chang et al. (2000)	The results identified herding in both bullish and bearish periods.

Empirical investigation of herding in cryptocurrency market under different market regimes.	Kumar (2020)	2013-2019	100 of the most capitalized cryptocurrencies	CSAD by Chang et al. (2000) and time-varying model by analyzing different market regimes (i.e.: up and down markets and high/low volatility).	Found that herding is pronounced when the market is either passing through stress or has become highly volatile. Anti-herding is found in a less volatile market or in a bullish market.
Herding behavior in the cryptocurrency market during COVID-19 pandemic: The role of media coverage.	Youssef et al. (2022)	2013-2020	43 of the most capitalized cryptocurrencies	CSAD by Chang et al. (2000)	Found evidence of herding for the entire sample period only during high volatility state. Moreover, during the COVID-19 crisis, results suggest that investors in the cryptocurrency market follow the consensus, thus, existing herding.
Herding intensity and volatility in cryptocurrency markets during the COVID-19.	Evrim Mandaci & Cagli (2022)	2018-2021	9 of the most capitalized cryptocurrencies	CSAD by Chang et al. (2000), the Patterson and Sharma (2006) statistics measuring of herding intensity and the Granger causality methodology with a Fourier approximation.	The results indicate a significant herding behavior, concentrating during the COVID-19 outbreak. The causality test results show that herding has a significant effect on market volatility.
Market Stress and Herding: A New Approach to the Cryptocurrency Market.	Raimundo Júnior et al. (2022)	2015-2020	80 of the most capitalized cryptocurrencies	CSSD by Christie and Huang (1995), CSAD by Chang et al. (2000) and Hwang and Salmon (2004)	The results identified a positive relationship between herding and market stress. Observing that herding was intense during the investigated period, including the first year of the COVID-19 pandemic.
COVID-19, Lockdowns and herding towards a cryptocurrency market-specific implied volatility index.	Rubbaniy et al. (2021)	2015-2020	101 of the most capitalized cryptocurrencies	CSAD by Chang et al. (2000), equally weighted cryptocurrency portfolio returns for market returns and VCRIX fear index	The results confirm the existence of herding behavior in the cryptocurrency market for the entire sample and show that herding asymmetry is present during both bullish and bearish regimes. Additionally, crypto investors seem to mimic the trading decisions of others during the COVID-19 pandemic.

Table 2 Empirical Evidence Comparison on Herding Behavior
Self-elaboration

2.4 Context

2.4.1 Macroeconomic context

The years between 2017 and 2022 will be the period analyzed for this dissertation. Within this timeframe, the world economy has seen many events that influenced the financial markets. Between 2017 and 2022, the global economic landscape continued to evolve with new challenges and developments. One notable aspect was the ongoing impact of the COVID-19 pandemic, which emerged in late 2019 and led to widespread disruptions across the world. Global GDP experienced a marked contraction in 2020 due to the pandemic, which was one of the most significant downturns since the Great Depression, with a contraction by roughly 3.5% in relation to the prior year (The World Bank, 2023). However, global GDP began to recover in 2021 as countries gradually reopened borders and economic activities resumed, albeit unevenly across different regions. This recovery was fueled by massive fiscal and monetary stimulus provided by governments and central banks worldwide, which led to concerns about rising inflation and debt levels (Moder & Fuentes, 2021; Szmigiera, 2021). Overall, the global GDP increased from 81.48 trillion USD in 2017 to 100.88 trillion USD in 2022, representing an increase of more than 23% in five years (The World Bank, 2023).

Stock and financial markets witnessed considerable volatility during this period, reflecting the uncertainty and rapid changes in the global economic environment. Initially, there was a sharp decline in stock markets globally at the onset of the pandemic in early 2020. However, markets rebounded strongly later in the year and into 2021, driven by the unprecedented monetary easing, fiscal stimulus, and optimism about economic recovery (Mishra, 2021).

Nonetheless, inflation dynamics became a prominent theme, with some economies experiencing higher inflation rates, prompting central banks to reassess their policy stances (The World Bank, 2021).

Political developments also played a significant role in shaping economic conditions. Elections, such as the US presidential election that marked the beginning of Donald Trump's administration in 2017, policy changes and geopolitical events, such as Brexit negotiations in 2018, influenced investor confidence and market dynamics and shifts in trade policies, added to economic risks (Mishra, 2021).

In essence, the period from 2017 to 2022 was a time of significant economic upheaval and transformation. The global economy faced unprecedented challenges, notably the COVID-19 pandemic, which profoundly impacted global GDP and financial markets. The recovery phase, influenced by substantial policy interventions, was marked by volatility and complexities, including inflation and geopolitical changes.

2.4.2 Cryptocurrency market

2.4.2.1 Origins and concept of cryptocurrencies

Cryptocurrencies, utilizing cryptography and decentralized networks, operate independently of governments or central banks, primarily on blockchain technology. Bitcoin, the pioneering cryptocurrency introduced by Satoshi Nakamoto, facilitates peer-to-peer transactions securely and transparently (Nakamoto, 2008). Since then, thousands of alternative cryptocurrencies, known as altcoins, have emerged, each with unique features (Buterin, 2013). The blockchain's versatility has led to innovations such as decentralized finance (DeFi), non-fungible tokens (NFTs), and smart contracts.

Cryptocurrencies typically have a predetermined and limited supply, akin to precious metals like gold, while fiat currencies are regulated by centralized authorities (Yermack, 2015). Transactions in cryptocurrencies are pseudonymous, offering privacy through wallet addresses, unlike fiat currencies, which often involve more transparent transactions (Catalini & Gans, 2019).

2.4.2.2 Market Dynamics

Cryptocurrencies are characterized by high volatility, influenced by factors like market sentiment, regulatory changes, and technological advancements (Poyser, 2017). The cryptocurrency market, despite its rapid growth, faces significant security challenges due to its decentralized and often unregulated nature.

Cybersecurity issues, including hacks and thefts, are recurrent, exacerbated by widespread fraud and scams like Ponzi schemes and phishing attacks (Bouri et al., 2019). Additionally, the market is witnessing a trend of consolidation, with larger platforms acquiring smaller ones, potentially impacting liquidity, competition, and raising concerns about market manipulation (Ajaz & Kumar, 2018).

Central banks worldwide are increasingly interested in cryptocurrencies and blockchain technology, exploring the development of Central Bank Digital Currencies (CBDCs). This trend acknowledges blockchain's potential benefits in enhancing payment systems' efficiency, security, and transparency (Corbet et al., 2019; Sharma & Kumar, 2019). However, integrating cryptocurrencies into the mainstream financial system presents challenges, including regulatory and monetary policy implications. Additionally, market liquidity in the cryptocurrency space varies significantly across different cryptocurrencies and trading platforms, with major ones like Bitcoin and Ethereum generally having higher liquidity, essential for stable market conditions and efficient price discovery (Mandaci & Cagli, 2022). Lastly, Bitcoin's dominance in the cryptocurrency market, often representing a significant portion of the total market capitalization, raises concerns due to its potential to disproportionately influence overall market dynamics. This concentration risk heightens volatility and systemic risks, worrying investors (Earle & Waugh, 2023).

In conclusion, the cryptocurrency market's evolution from 2017 to 2022 has been marked by significant growth, innovation, and challenges. Issues such as security breaches, fraud, market consolidation, central bank involvement, liquidity concerns, and the concentration of major cryptocurrencies like Bitcoin have shaped the market's dynamics and will likely continue to influence its trajectory in the future.

2.5 Hypothesis

H1: Herding behavior is significantly present in the cryptocurrency market during the period of 2017 to 2019.

The hypothesis that herding behavior is significantly present in the cryptocurrency market, even before the pandemic years, is supported by several key aspects found in the existing literature. Based on the literature, it can be concluded that the cryptocurrency market's speculative nature stems from unregulated risks and technological challenges (Fry & Cheah, 2016). Given that the cryptocurrency market is marked by a deficient legal framework and a shortage of reliable information, investors frequently enter the market without a comprehensive understanding of the associated risks (Bouri et al., 2019). Therefore, the validation of this hypothesis is relevant as cryptocurrencies commonly demonstrate remarkable returns and significant volatility, often lacking clear justifying factors (Kaiser & Stöckl, 2020), which could possibly be associated with the presence of herding behavior in the market, regardless of the COVID-19 pandemic effects in the posterior years (2020 to 2022).

In the macroeconomic context, the cryptocurrency market experienced a surge in growth and attention during the period from 2017 to 2019. This era saw a proliferation of new digital tokens through ICOs, attracting investors of all types. Amidst global economic uncertainties and heightened market volatility, the speculative nature of cryptocurrencies became more apparent (da Gama Silva et al., 2019). This environment provided fertile ground for herding behavior, as investors sought to capitalize on perceived trends and opportunities. Consequently, the macroeconomic context of this period reinforced the presence of herding behavior in the cryptocurrency market, supporting the hypothesis.

Moreover, a significant portion of the literature (Ballis & Drakos, 2020; Haryanto et al., 2020; Kaiser & Stöckl, 2020; Mandaci & Cagli, 2022; Raimundo Júnior et al., 2022; Rubbaniy et al., 2021; Vidal-Tomás et al., 2019; Youssef & Waked, 2022) reports robust evidence of herding in the cryptocurrency market, reinforcing the hypothesis. This evidence is consistent across various research methods and market conditions, including both bearish and bullish periods as well as times of high market volatility. Such widespread empirical support, derived from a multitude of studies, underscores the presence of herding behavior in the cryptocurrency market, lending substantial credibility to the proposed hypothesis.

H2: The COVID-19 pandemic increased investors' herding behavior in the cryptocurrency market.

The COVID-19 pandemic created unprecedented market volatility and uncertainty, challenging the assumptions of market efficiency. This sets the stage for investigating whether herding behavior, a phenomenon often associated with irrational decision-making, becomes more prevalent in response to external shocks like the pandemic.

Empirical evidence, while mixed, offers support for this hypothesis. Several studies have noted a tendency towards herding behavior in the cryptocurrency market during the pandemic (Mandaci & Cagli, 2022; Raimundo Júnior et al., 2022; Rubbaniy et al., 2021; Youssef & Waked, 2022). This trend aligns with the broader patterns observed in financial markets during crises, where investors often resort to mimicking the decisions of the majority as a coping mechanism to deal with uncertainty and information asymmetry. In the context of the COVID-19 pandemic, this tendency could have been further heightened due to the rapid and significant changes in market conditions, alongside the influx of new and less experienced investors into the cryptocurrency market (Mandaci & Cagli, 2022).

Moreover, the unique characteristics of the cryptocurrency market, such as its relative novelty, lack of regulation, and high volatility, could exacerbate the propensity for herding behavior. In such an environment, where traditional financial analysis and historical data are less applicable, investors might be more inclined to base their decisions on the observable actions of others, particularly in response to sudden market shocks and news about the pandemic (Earle & Waugh, 2023). Therefore, despite the conflicting empirical results, the context of the COVID-19 pandemic, combined with the inherent characteristics of the cryptocurrency market, provides a compelling argument for the increased prevalence of herding behavior among investors during this period.

Chapter 3 Data and Methodology

3.1 Quantitative Model

I will employ a quantitative model in this thesis for its systematic and objective approach to financial data analysis. Utilizing statistical techniques and mathematical models, I can effectively test hypotheses and uncover underlying trends (Kumar, 2020). Despite its advantages, quantitative modeling has drawbacks such as reliance on historical data, which may not accurately reflect current market conditions or anticipate future trends (Bikhchandani & Sharma, 2000). However, this approach aligns with industry standards in financial analysis and risk management, ensuring the relevance of my findings to real-world scenarios. Furthermore, the precision and rigor of quantitative methods make them ideal for exploring complex financial markets.

3.2 Data

This thesis adopts a methodology grounded in the analysis of secondary data, focusing on eight key cryptocurrencies that are pivotal in the cryptocurrency market due to their substantial market capitalization and established presence, utilizing panel data that encompasses both time-series and cross-sectional elements. These include Bitcoin (BTC), Ethereum (ETH), Binance (BNB), Stellar (XLM), Dogecoin (DOGE), Ripple (XRP), Litecoin (LTC), and Monero (XMR). These cryptocurrencies were selected not only based on their robust market capitalization but also their establishment in the market before August 2017, ensuring the availability of consistent and comprehensive data throughout the research. To better understand the eight cryptocurrencies selected for this study, please refer to Table 3 below. It succinctly presents key details such as their launch year, primary purpose, and unique features, offering a quick overview of each currency's distinctive attributes and roles in the cryptocurrency market.

Cryptocurrency	Launch Year	Primary Purpose	Unique Features
Bitcoin (BTC)	2009	Digital Currency	First cryptocurrency, decentralized
Ethereum (ETH)	2015	Platform for Decentralized Apps	Smart contracts, Ethereum Virtual Machine
Stellar (XLM)	2014	Cross-Border Transactions	Low-cost, fast transactions, Lumens (XLM)
Dogecoin (DOGE)	2013	Digital Currency with a Fun Side	Unlimited supply, meme-culture integration
Ripple (XRP)	2012	International Payment Settlement	Fast and efficient, RippleNet network
Litecoin (LTC)	2011	Digital Currency	Faster transaction times than Bitcoin
Monero (XMR)	2014	Privacy-focused Digital Currency	Untraceable, private transactions
Binance (BNB)	2017	Utility Token for Binance Exchange	Reduced fees on Binance, token burn mechanism

Table 3 Summary Cryptocurrencies Characteristics
Self-Elaboration.

In addition to individual cryptocurrencies, the study incorporates the CCi30 index (www.cci30.com), a key benchmark comprising the top 30 cryptocurrencies by market capitalization, to provide a broad perspective on cryptocurrency market dynamics. Functioning similarly to the S&P 500 for the U.S. stock market, the CCi30 offers an up-to-date, market cap-weighted snapshot of the sector's performance. This index is crucial for evaluating market trends, investment opportunities, and assessing risks and returns in the volatile cryptocurrency market.

For empirical analysis, this study aggregates the closing daily prices in USD for these cryptocurrencies. The data, spanning from August 1, 2017, to

December 31, 2022 (1975 days), is extracted from reliable sources such as coinmarketcap.com and cci30.com. These platforms are frequently used in empirical research, as indicated by various academic studies (Ajaz & Kumar, 2018; Bouri et al., 2019; da Gama Silva et al., 2019; Kaiser & Stöckl, 2020; Kumar, 2020; Raimundo Júnior et al., 2022; Rubbaniy et al., 2021; Vidal-Tomás et al., 2019; Youssef & Waked, 2022). In addition, this research emphasizes the importance of including outliers in the data set, as their analysis is key to understanding herding behavior in the cryptocurrency market, particularly during unusual market conditions. This approach allows for a thorough examination of market patterns, offering significant insights into the dynamics of herding behavior.

3.3 Variables

Calculations were conducted using the daily closing prices of the selected cryptocurrencies and the CCi30 index for the period from August 1, 2017, to December 31, 2022. With this data, I was able to calculate the daily return for all currencies across this period, which became the main variable for this thesis. All data were transformed into a log return form.

The formula used for this purpose was:

$$Daily\ Return\ (Rd) = ln\ \frac{CP_t}{CP_{t-1}} \times 100$$

Where CP_t represents the closing price on a given day t, and CP_{t-1} is the closing price from the previous day. The logarithmic (log) returns were chosen for this analysis, as they offer uniformity in evaluating daily closing prices across different cryptocurrencies. Unlike simple returns, log returns provide a consistent measure that is not disproportionately influenced by high-value assets like Bitcoin. This uniform approach is vital for comparative analysis, ensuring that the impact of each cryptocurrency, regardless of its market value, is appropriately assessed without skewing the results. This method aligns with standard practices in financial research, offering a more balanced and accurate depiction of market dynamics (Ajaz & Kumar, 2018; Bouri et al., 2019; da Gama Silva et al., 2019; Kaiser & Stöckl, 2020; Kumar, 2020; Raimundo Júnior et al., 2022; Rubbaniy et al., 2021; Youssef & Waked, 2022).

Afterwards, this analysis was divided in two different periods: the first one encompassing the pre-COVID period from 2017 until 2019 and a second one encompassing the COVID period from 2020 until 2022. The goal with this division is to analyze the impact of the COVID-19 pandemic on the herding behavior of investors in the cryptocurrency market.

3.4 Methodology

The methodology used in this research is the Cross-Sectional Absolute Deviation (CSAD), proposed by Chang et al. (2000). This method utilizes non-linear regression to analyze the correlation between the dispersion of asset returns, gauged by the absolute deviation from returns, and market returns. CSAD is an improvement of the prior method, Cross-Sectional Standard Deviation (CSSD), proposed by Christie & Huang (1995).

CCSD method, while innovative for detecting herding behavior in financial markets, has several inherent limitations as it assumes a level of homogeneity among investors, not accounting for the diversity in their behaviors and motivations (Economou et al., 2011). On the other hand, CSAD addresses this issue by using the absolute deviation of returns, offering a more robust measure against extreme values. This makes CSAD particularly suitable for the cryptocurrency market, as it better accommodates the high volatility and frequent price swings (Vidal-Tomás et al., 2019).

The CSAD model is expressed by the following equations:

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

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

Where γ_1 and γ_2 are the coefficients that measure the impact of market return (both linear and squared terms), $|R_{m,t}|$ is the absolute value of the market return at time t and captures the direct impact of market return magnitude on deviation, and $R_{m,t}^2$ is the squared market return at time t and represents the non-linear effects of market return on deviation.

In addition to the CSAD method proposed by Chang et al. (2000), yet another variation to this model was suggested by Chiang & Zheng (2010). This variation was a significant development in analyzing herding behavior in financial markets as it enhances robustness of the original CSAD approach by incorporating market states into the analysis. The variation is represented by the following equation:

$$CSAD_t = \propto\ + \gamma_1 R_{m,t} + \ \gamma_2\left|R_{m,t}\right| + \ \gamma_3 R_{m,t}^2 + \varepsilon^t$$

Where $\gamma_3 R_{m,t}^2$ includes the squared market return to measure the non-linear effects in a more comprehensive manner, explicitly accounts for the linear impact of market returns, providing a more granular analysis of how returns influence herding behavior. It allows for a differentiated understanding of herding during periods of market gains and losses, which is crucial in the highly volatile and reactive cryptocurrency market (Haryanto et al., 2020;

Raimundo Júnior et al., 2022). In sum, if the results present a negative and statistically significant coefficient γ_3, then, herding behavior is present.

For this thesis, the empirical tests will be divided into two sections: (a) the verification of the presence of herding behavior in the cryptocurrency market on the period before the COVID-19 pandemic, encompassing the years of 2017, 2018 and 2019; and (b) the variation of the herding intensity in the cryptocurrency market (if increased or decreased) during the pandemic years of 2020, 2021 and 2022.

For both parts (a) and (b), the analysis of the presence and intensity of herding behavior will be conducted by using the CSAD model proposed by Chang et al., (2000) and complemented with the variation to the CSAD method proposed by Chiang & Zheng (2010) for more robust conclusions. The rational for this choice follows current literature (Bouri et al., 2019; da Gama Silva et al., 2019; Kaiser & Stöckl, 2020; Raimundo Júnior et al., 2022; Vidal-Tomás et al., 2019) and puts value on the simplicity of the methodology to achieve clear conclusions.

This analysis opts for Ordinary Least Squares (OLS) for its regression due to its efficacy in managing linear relationships and delivering clear and interpretable results in the cryptocurrency market (Kumar, 2020; Raimundo Júnior et al., 2022). In contrast,e Generalized Least Squares (GLS) accommodates for heteroscedasticity and autocorrelation, its implementation requires specifying the covariance structure of errors, which can be complex. Furthermore, GLS may introduce additional computational burdens and model complexity without necessarily offering substantial improvements in results interpretation. Thus, considering the practical constraints and the relative simplicity of OLS, it remains the preferred approach for many researchers and practitioners analyzing panel data in the cryptocurrency market.

Therefore, the below formulas are going to be applied to test the hypothesis proposed by this thesis:

(i) $CSADt = \frac{\sum_{i=1}^{N} |R_{i,t} - R_{m,t}|}{N}$

(ii) $CSAD_t = \propto + \gamma_1 |R_{m,t}| + \gamma_2 R^2_{m,t} + \varepsilon^t$

(iii) $CSAD_t = \propto + \gamma_1 R_{m,t} + \gamma_2 \left|R_{m,t}\right| + \gamma_3 R^2_{m,t} + \varepsilon^t$

3.5 Software

For this thesis, Microsoft Excel was chosen for cryptocurrency data analysis due to its accessibility and user-friendliness. While tools like R, Python, and SPSS offer advanced capabilities, their complexity is unnecessary for the sample size. Excel's intuitive interface efficiently manages and visualizes data, striking a balance between sophisticated analysis and practical usability, suitable for the thesis's scope and resources (Guerrero, 2019; Mélard, 2014).

Chapter 4 Results

4.1 Descriptive statistics

A profound understanding of the fluctuations is gained by assessing the variables' daily returns' minimum and maximum values (See Table 4 below). For example, DOGE, known as a "meme coin," exhibits a striking volatility of 203.15%, while the average volatility across the sample is 95.86%. Such significant daily shifts in returns imply that behavioral dynamics are at play in influencing cryptocurrency pricing.

	BTC	ETH	BNB	XRP	DOGE	XLM	LTC	XMR	CCi30
Minimum	-46.47%	-55.07%	-54.31%	-55.05%	-51.51%	-41.00%	-44.91%	-53.42%	-48.45%
Maximum	22.51%	23.47%	67.52%	60.69%	151.64%	66.68%	38.93%	35.24%	19.57%

Table 4: Maximum and minimum daily returns from 2017 to 2022

In order to complete the analysis of the selected sample, the descriptive statistics of the selected group of eight cryptocurrencies and the CCi30 market benchmark of the daily returns of the market are displayed in Table 5 below:

	BTC	*ETH*	*BNB*	*XRP*	*DOGE*	*XLM*	*LTC*	*XMR*	*CCi30*
Mean	0.00092	0.00086	0.00396	0.00034	0.00186	0.00069	0.00026	0.00062	0.00038
Std. Dev.	4.07%	5.16%	6.73%	6.34%	7.95%	6.59%	5.64%	5.65%	4.64%
Median	0.00123	0.00081	0.00107	-0.00105	-0.00108	-0.00114	7.3E-05	0.00183	0.00312
Minimum	-0.46473	-0.5507	-0.54308	-0.5505	-0.51511	-0.40995	-0.4491	-0.5342	-0.4845
Maximum	0.22512	0.23474	0.67517	0.60689	1.51638	0.66677	0.38932	0.35242	0.19568
Kurtosis	11.3219	9.34124	15.9747	15.9608	79.8485	14.0944	8.78347	10.4634	9.98623
Skewness	-0.79354	-0.8876	0.92576	0.81733	4.5183	1.24538	-0.2425	-0.65002	-1.2978

Table 5: Descriptive statistics of Daily Returns from 2017 to 2022

The descriptive statistics for the various cryptocurrencies offer a nuanced view of their performance characteristics. For instance, the average return, or mean, gives us an initial impression of what investors might expect. Bitcoin (BTC) and Ethereum (ETH), typically seen as market leaders, show modest mean returns, 0.00092 and 0.00086 respectively, suggesting they have steady, albeit not spectacular, average price changes. In contrast, coins like Binance (BNB) demonstrate a higher mean (0.00396) indicating stronger average price movements, which might attract investors looking for higher returns despite the increased risk.

Volatility, captured by the standard deviation, is most pronounced in DOGE (0.0795) suggesting that its price is the most variable and thus the riskiest among the cryptocurrencies considered. A high standard deviation often signals that an asset's price can swing widely, which could be both an opportunity and a threat to investors.

When we look at the median returns, which tell us the middle value of the dataset, it is noteworthy that Ripple (XRP), Dogecoin (DOGE), and Stellar (XLM) have negative medians (-0.00105, -0.00108, and -0.00114 respectively). This implies that more than half of the price changes recorded during the period were losses, a potentially worrying sign for investors seeking consistent gains.

Exploring the range of returns, as indicated by the minimum and maximum values, BNB and DOGE stand out for their wide price movements, a difference of 121.83% and 203.15% respectively. This suggests that investors in these cryptocurrencies might have experienced some of the most extreme highs and lows, potentially leading to significant gains or losses.

The shape of the return distributions is described by kurtosis and skewness. Kurtosis is particularly extreme for DOGE (79.84) indicating a high likelihood of outlier returns which could dramatically affect an investment's outcome.

High kurtosis in investment returns can be a double-edged sword, with the potential for both unusually large gains and losses. On the other hand, skewness tells us about the asymmetry of the distribution of returns. BNB's positive skew (0.9257) suggests that while most of its returns are modest losses, the chance of a large gain is not negligible. Meanwhile, the negative skew for BTC (-0.7935) implies that it tends to offer smaller, more frequent gains rather than large windfalls.

Analyzing the non-currencies variable, the statistics indicates that the CCi30 has a relatively moderate mean (0.00038) and standard deviation (0.04642), with a high median (0.00312) compared to most individual cryptocurrencies, suggesting that it may offer more stable returns than investing in a single cryptocurrency.

Overall, these statistics paint a picture of a cryptocurrency market with a diverse array of risk and return profiles. From the more stable, consistent performers to the volatile, potentially high-return options, investors have a range of choices that correspond to their risk appetite and investment strategy, which reflects a typical sample and period for the study of cryptocurrencies.

4.2 Main results

To test the first hypothesis (*H1: Herding behavior is significantly present in the cryptocurrency market during the period of 2017 to 2019),* the CSAD model of Chang et al. (2000) and the variation of Chiang and Zheng (2010) were used. Herding presence is tested through the using of equations (i), (ii) and (iii) prior mentioned and the results extracted from the model are displayed in Table 6 below:

	Coefficients	Standard Error	t Stat	P-value
Intercept	0.017841321	0.001057008	16.879083	1.47983E-55
Absolute market return (Y1)	0.204947469	0.041192071	4.97541068	7.83704E-07
Squared market return (Y2)	-0.212819986	0.2696123	-0.78935563	0.430117775

Table 6: Regression of equation (ii) for the pre-COVID-19 period, from years 2017 to 2019.

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

Statistical significance at the 5% level

According to equation (ii), for the pre-COVID period corresponding to the years 2017 to 2019, it is possible to detect a positive coefficient on the linear term γ_1, meaning that CSAD increases in the same direction as the market. On the other hand, the non-linear term γ_2 presents a negative coefficient, meaning that the increase in CSAD is negatively correlated with the market, suggesting strong presence of herding behavior. However, despite the significant t-value presented for γ_2 (-0.7893), the dependable variable γ_2 is not statistically significant at conventional level of 0.05, as the p-value achieved is 0.4301, suggesting a weaker or no liner relationship with CSAD.

For the purpose of revalidating the results, herding presence is also tested using equation (iii). The results extracted from the model are displayed in Table 7 below:

	Coefficients	Standard Error	t Stat	P-value
Intercept	0.018269075	0.001034894	17.6530896	6.84048E-60
Market return (Y1)	0.090924195	0.013943321	6.52098536	1.17952E-10
Absolute market return (Y2)	0.155552879	0.040955751	3.79807172	0.000155901
Squared market return (Y3)	0.324803906	0.276040435	1.17665336	0.239653885

Table 7: Regression of equation (iii) for the pre-COVID-19 period, from years 2017 to 2019.

$$CSAD_t = \propto + \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 R_{m,t}^2 + \varepsilon^t$$

Statistical significance at the 5% level

In this case, the results do not confirm the presence of herding as the coefficient γ_3 shows a positive relationship with the independent variable CSAD, meaning that CSAD increases in the squared market return (γ_3)

coefficient. Therefore, this does not suggest the presence of herding as the p-value found is greater (0.2395) than the statistically significance level of 0.05.

To test the second hypothesis (*H2: The COVID-19 pandemic increased investors' herding behavior in the cryptocurrency market),* the same equations (i), (ii), (iii) were used for the COVID-19 pandemic period but now using the data corresponding to the years 2019 to 2022 exclusively. The results extracted from the model are displayed in Table 8 below:

	Coefficients	*Standard Error*	*t Stat*	*P-value*
Intercept	0.013925679	0.000755426	18.4342066	2.95358E-66
Absolute market return (Y1)	0.205542506	0.023146499	8.88006902	2.70119E-18
Squared market return (Y2)	-0.202263315	0.088441272	-2.2869788	0.022388238

Table 8: Regression of equation (ii) for the COVID-19 period, from years 2019 to 2022.

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

Statistical significance at the 5% level

Applying equation (ii), similarly to what was observed in the pre-COVID period, the non-linear term γ_2 presents a negative coefficient, meaning that the increase in CSAD is negatively correlated with the market, suggesting strong presence of herding behavior. Additionally, the coefficient for γ_2 is statistically significant as indicated by a t-statistic of -2.287 and a corresponding p-value of 0.0224, which is less than 0.05. We can conclude that the variable γ_2 has a statistically significant effect on the dependent variable at the 5% significance level. Thus, the results for equation (ii) can be an indication of herding behavior with a high degree of confidence during the period and can be an indication of "increase" of herding behavior compared to the prior period.

In the same way, for revalidating the results, herding presence is also tested using equation (iii). The results extracted from the model are displayed in Table 9 below:

	Coefficients	Standard Error	t Stat	P-value
Intercept	0.013766278	0.000743875	18.5061613	1.08905E-66
Market return (Y1)	0.068558528	0.011348422	6.04123879	2.09708E-09
Absolute market return (Y2)	0.196926684	0.022822844	8.62849012	2.17259E-17
Squared market return (Y3)	-0.025483085	0.091821719	-0.27752785	0.781427544

Table 9: Regression of equation (iii) for the COVID-19 period, from years 2019 to 2022.

$$CSAD_t = \propto + \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 R_{m,t}^2 + \varepsilon^t$$

Statistical significance at the 5% level

For the period of 2019 to 2022, on the contrary of what was observed for equation (iii) during the pre-COVID period, the coefficient γ_3 is negative, suggesting strong evidence of the herding behavior, which would at first observation confirm the hypothesis of an "increased" herding when compared to the prior period. However, as has happened to the other coefficients, the p-value (0.7815) for a significance value of 0.05 was not achieve for equation (iii) either. Therefore, the results despite indicating a strong presence of augmented herding, it cannot be considered significant for the data collected.

Overall, our main results indicate an absence of herding behavior in neither period. In this way, for the purpose of strengthening the thesis' results, although keeping the research questions and hypothesis, an additional test using equation (iii) was conducted to test all data comprising the full temporal period from 2017 to 2022. The results extracted from the model are displayed in Table 10 below:

	Coefficients	Standard Error	t Stat	P-value
Intercept	0.015525188	0.00059678	26.01486302	1.7406E-128
Market return (Y1)	0.077765462	0.00886161	8.775541618	3.61277E-18
Absolute market return (Y2)	0.193430265	0.01871997	10.33282948	2.07951E-24
Squared market return (Y3)	0.020627085	0.08888664	0.232060583	0.816515087

Table 10: Regression of equation (iii) for the whole sample period from 2019 to 2022.

$$CSAD_t = \propto + \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 R_{m,t}^2 + \varepsilon^t$$

Statistical significance at the 5% level

Based on the data, γ_3 is not statistically significant at the conventional significance level of 0.05. This is indicated by a t-statistic of 0.2321 and a corresponding p-value of 0.8165, which is greater than 0.05. Therefore, this result is aligned with the four scenarios proposed in this thesis, in which confirms the non-significance of the herding behavior for the period.

Additionally, by assessing the global goodness of the regression models, several key statistics provide insights into their performance, which hints to the overall results of the non-significance of the herding behavior of the sample. For instance, for all the models, the R-squared is weak, representing a low autocorrelation between the dependent and independent variables, which may be a warning for imprecise predictions. This lack of significance may be attributed to potential autocorrelation issues, as indicated by the non-random pattern observed in the residuals. Autocorrelation can inflate standard errors and lead to underestimated p-values, potentially resulting in non-significant coefficients.

4.3 Discussion

4.3.1 Discussion on Hypothesis 1 results

The results extracted from the application of the CSAD models devised by Chang et al. (2000) and Chiang & Zheng, (2010) do not validate Hypothesis 1, that herding is significantly present in the cryptocurrency market between the years 2017 and 2019. Overall, the investigation into herding behavior within the cryptocurrency market, specifically during the pre-COVID-19 years of 2017 to 2019, yields intriguing insights, albeit not supporting the presence of herding as initially hypothesized.

Despite the speculative nature and significant volatility of the cryptocurrency market, which some theorists like Bouri et al. (2019) and Fry & Cheah (2016) suggest could lead to herding behavior due to unregulated risks and technological challenges, the empirical evidence from this thesis does not corroborate herding tendencies during the specified period. This finding is particularly notable given the robust evidence of herding presented by a substantial portion of the literature, with studies such as those by (Ballis & Drakos, 2020; Kaiser & Stöckl, 2020), which highlight the presence of herding across various market conditions and cryptocurrencies.

This divergence from the expected outcomes, despite employing a methodology shared across the relevant literature, may be attributed to several factors (Ballis & Drakos, 2020; Coskun et al., 2020; da Gama Silva et al., 2019; Haryanto et al., 2020; Kaiser & Stöckl, 2020; Mandaci & Cagli, 2022; Raimundo Júnior et al., 2022; Rubbaniy et al., 2021; Vidal-Tomás et al., 2019; Youssef & Waked, 2022). Firstly, the inherent volatility and speculative nature of the cryptocurrency market may mask or dilute the effects of herding behavior, making it difficult to detect through traditional models. Furthermore, the chosen period for analysis may exhibit unique market dynamics not conducive to herding, possibly influenced by external economic factors such as the cryptocurrency market's positive results starting in 2017 marked by significant growth and innovation to the sector.

Moreover, the mixed evidence of herding in the broader literature points to the complexity of the phenomenon and the need for nuanced approaches in its study. While nearly 67% of examined studies report evidence of herding, the presence of contradictory findings and methodological diversity underscores the challenge in drawing definitive conclusions (Bouri et al., 2019; Coskun et al., 2020; da Gama Silva et al., 2019; Kumar, 2020). This is further complicated by the evolving regulatory and technological landscape of cryptocurrencies, which may influence investor behavior in unpredictable ways.

4.3.2 Discussion on Hypothesis 2 results

The second hypothesis of the thesis, which posits that the COVID-19 pandemic has increased herding behavior among investors in the cryptocurrency market, is also not valid. Despite the tumultuous period of 2020 to 2022, characterized by significant economic upheaval, market volatility, and the unprecedented challenges of the COVID-19 pandemic, the empirical analysis conducted does not conclusively support an increase in herding behavior during the pandemic years.

This conclusion is drawn against the backdrop of existing literature, where a substantial body of research suggests a propensity for herding behavior in financial markets during times of crisis and high uncertainty. Notably, studies by Mandaci & Cagli (2022) and Raimundo Júnior et al. (2022) highlight the inclination of investors to engage in herding during the pandemic, driven by the market's volatility and the influx of new, potentially less experienced investors. Such conditions, coupled with the cryptocurrency market's inherent characteristics—its novelty, lack of regulation, and predisposition to high volatility—would ostensibly provide fertile ground for herding.

Analyzing the macroeconomic context for this hypothesis, such result can be explained by the cryptocurrency market's unique response compared to traditional financial markets, whereas the pandemic period would not be categorized as a "period of crisis" for the market. Unlike conventional assets, cryptocurrencies operated independently during the crisis due to their decentralized nature and lack of direct correlation with macroeconomic indicators. The pandemic spurred increased interest in digital assets as alternative investments, leading to heightened trading activity and adoption rates. In the same way, the mixed evidence found in the literature, with some studies indicating herding while others not, underscores the complexity of assessing herding behavior and the influence of external shocks on market dynamics (Mandaci & Cagli, 2022; Raimundo Júnior et al., 2022; Rubbaniy et al., 2021; Youssef & Waked, 2022).

Thus, while the hypothesis theorized an increase in herding behavior during the pandemic, the empirical evidence analyzed does not support this claim. Overall, while the pandemic created conditions that could theoretically heighten herding behavior in the cryptocurrency market, the empirical analysis conducted in this thesis does not support a significant increase in herding during the years 2020 to 2022.

Chapter 5 Conclusion

5.1 Main conclusions

Despite the widespread speculation and inherent volatility that characterize the cryptocurrency market, the findings of this thesis challenge the prevailing assumption of pervasive herding behavior, both during the pre-pandemic years of 2017 to 2019 and throughout the period of 2020 to 2022. Therefore, aligned with the group of 17% of the studies prior presented (Coskun et al., 2020; da Gama Silva et al., 2019), the findings revealed no significant herding behavior in cryptocurrencies, suggesting a need for new models to better understand these dynamics.

This thesis significantly advances the study of herding behavior in the volatile and speculative cryptocurrency market, addressing a notable research gap. Through empirical analysis using CSAD models, it provides insights into investor behavior amid external shocks like the COVID-19 pandemic, challenging the assumed prevalence of herding in this domain. In conclusion, this thesis provides empirical evidence that contradicts the expected outcomes and calls for a nuanced understanding of investor behavior in this market.

5.2 Implications for management

Despite the absence of significant herding behavior found in the study, policymakers and regulators can still derive valuable insights for shaping regulations in the cryptocurrency market. The research underscores the importance of understanding market dynamics and promoting financial literacy among investors. Therefore, policymakers may consider focusing on initiatives that enhance investor education and critical thinking skills, ensuring that regulations reflect the unique characteristics of cryptocurrencies while supporting market integrity and innovation.

While the study did not find significant evidence of herding behavior, inexperienced traders, particularly prevalent in the cryptocurrency market, can benefit from a deeper engagement with educational resources and a shift towards strategies that emphasize critical thinking over following market trends. In the same way, for both individual and institutional investors, the research findings emphasize the significance of thorough market analysis in managing portfolio risk, especially in the context of cryptocurrencies as alternative investments.

In conclusion, while the study did not find significant evidence of herding behavior in the cryptocurrency market, the implications for policymakers, regulators, inexperienced traders, and investors remain significant. By promoting financial literacy, enhancing investor education, and encouraging analytical engagement with the market, stakeholders can contribute to the development of a more mature, stable, and innovative cryptocurrency market ecosystem.

5.3 Limitations of research

The research methodology of this thesis, while designed to explore herding behavior within the cryptocurrency market through the analysis of secondary data on eight major cryptocurrencies and the CCi30 index, presents certain limitations. Focusing on a select group of cryptocurrencies based on market capitalization and historical establishment limits the scope to a subset of the market that, while significant, may not capture the full spectrum of investor behavior across the broader, diverse cryptocurrency landscape. This selection criterion, aimed at ensuring data consistency and comprehensiveness, might overlook emerging cryptocurrencies that could exhibit different patterns of herding behavior.

Moreover, the reliance on daily closing prices and the application of the CSAD model, supplemented by OLS regression, confines the analysis to specific methodological frameworks. While these choices align with established financial research practices and aim to provide a balanced and accurate depiction of market dynamics, they may not fully encompass the multifaceted and rapidly evolving nature of cryptocurrency markets. Additionally, the division of the analysis into pre-COVID and during-COVID periods, intended to assess the pandemic's impact on herding behavior, introduces a temporal limitation that may not account for long-term behavioral shifts or the immediate aftermath of the pandemic period.

5.4 Future research

Building on the findings, conclusion, and contributions of this thesis, future research in the domain of cryptocurrency markets and herding behavior should consider expanding the scope of analysis to include a broader array of cryptocurrencies, particularly those emerging after 2017, to capture a more comprehensive view of market dynamics. Moreover, incorporating advanced statistical methods and leveraging software with capabilities beyond those of Microsoft Excel could enhance the depth and breadth of data analysis, allowing for more nuanced interpretations of complex behaviors. Further studies might also explore the psychological and socio-economic factors influencing individual and collective investment decisions in the cryptocurrency market, integrating behavioral finance theories with insights from psychology and sociology.

Additionally, longitudinal studies assessing herding behavior over extended periods could provide valuable insights into how investor behavior evolves in response to regulatory changes, technological advancements, and shifts in the global economic landscape. This approach would not only build upon the current thesis's contributions but also offer a richer, more detailed understanding of the factors driving investor behavior in the rapidly evolving cryptocurrency market.

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Appendix

I. Origins and concept of cryptocurrencies

A cryptocurrency is a form of digital or virtual currency that uses cryptography for security and operates on a decentralized network of computers. Unlike traditional currencies issued by governments and central banks, cryptocurrencies are typically based on blockchain technology, which is a distributed ledger that records all transactions across a network of computers. The decentralized nature of cryptocurrencies means that no single entity, such as a government or financial institution, has control over the entire system.

The inception of cryptocurrencies can be traced back to the publication of the Bitcoin whitepaper (Nakamoto, 2008) by an individual or group using the pseudonym Satoshi Nakamoto in 2008. Bitcoin, the first decentralized cryptocurrency, was designed to operate on a peer-to-peer network, enabling secure, transparent, and borderless transactions without the need for intermediaries like banks. Since the advent of Bitcoin, thousands of alternative cryptocurrencies, often referred to as altcoins, have been created, each with its own unique features, purposes, and underlying technologies (Buterin, 2013). Additionally, blockchain uses have exploded via the creation of decentralized finance (DeFi) applications, non-fungible tokens (NFTs), and smart contracts.

Cryptocurrencies often have a predetermined and limited supply, defined by algorithms to introduce scarcity, like precious metals like gold (Yermack, 2015). In contrast, fiat currencies are issued and regulated by centralized authorities, allowing for direct control over the money supply and circulation by the Central Banks. Cryptocurrency transactions are pseudonymous, with wallet addresses used, providing a degree of privacy. On the other hand, fiat currency transactions, especially within traditional banking systems, are often more transparent, with financial institutions maintaining records of account holders' identities (Catalini & Gans, 2019).

II. Blockchain technology

Blockchain technology is a revolutionary concept that serves as the backbone for various cryptocurrencies, but its applications extend far beyond digital currencies. At its core, a blockchain is a decentralized and distributed ledger that records transactions across a network of computers in a secure and transparent manner (Bouri et al., 2019). The term "blockchain" is derived from the way data is structured in blocks, and each block contains a list of transactions. Once a block is completed, it is linked to the previous block, forming a chain of blocks, thus ensuring the immutability and integrity of the entire transaction history (Pass et al., 2017).

There are several ways to build a blockchain network, mainly the technology can work on two different types: permissionless and permission basis. The fundamental distinction between them lies in the accessibility and control mechanisms governing these networks. In a permissionless blockchain, such as Bitcoin, participation is open to anyone without the need for approval. This openness fosters decentralization, as individuals, often referred to as nodes or miners, can freely join, validate transactions, and contribute to the consensus process (Aysan & Bergigui, 2021). On the other hand, permissioned blockchains operate with restrictions on participation. Individuals seeking entry into a permissioned blockchain network must obtain permission or an invitation. These networks often have a central governing entity or organization that regulates participation, executes consensus protocols, and oversees the maintenance of the shared ledger. While permissioned blockchains sacrifice some decentralization, they enhance trust among participants through controlled access (Rashid, 2021).

The primary benefits of the blockchain technology lie in its decentralization of transaction authentication, streamlining a process typically requiring third-party intervention, such as banks or brokers. The consensus mechanisms are key to the blockchain technology by ensuring that all participants in a network agree on the validity of transactions and the order in which they are added to the shared ledger. The main consensus mechanisms are the Proof of Work (PoW) and the Proof of Stake (PoS). In the PoW system, network participants collaborate to solve cryptographic puzzles to add new information (blocks), a process commonly known as "mining," demanding significant computational resources and electricity. Conversely, PoS operates as a transaction validation system, requiring evidence of asset ownership to validate transactions in a process called "forging," where validators receive fees for their services (Krause et al., 2017).

In essence, the blockchain process unfolds as follows: a network node adds new information to the blockchain database, creating a new data block. This block is then transmitted to the entire network in encrypted form using cryptography, ensuring transaction details remain confidential (Krause et al., 2017). Network members validate the block through an algorithmic method (PoW or PoS), and once confirmed, a new block is officially appended to the chain.

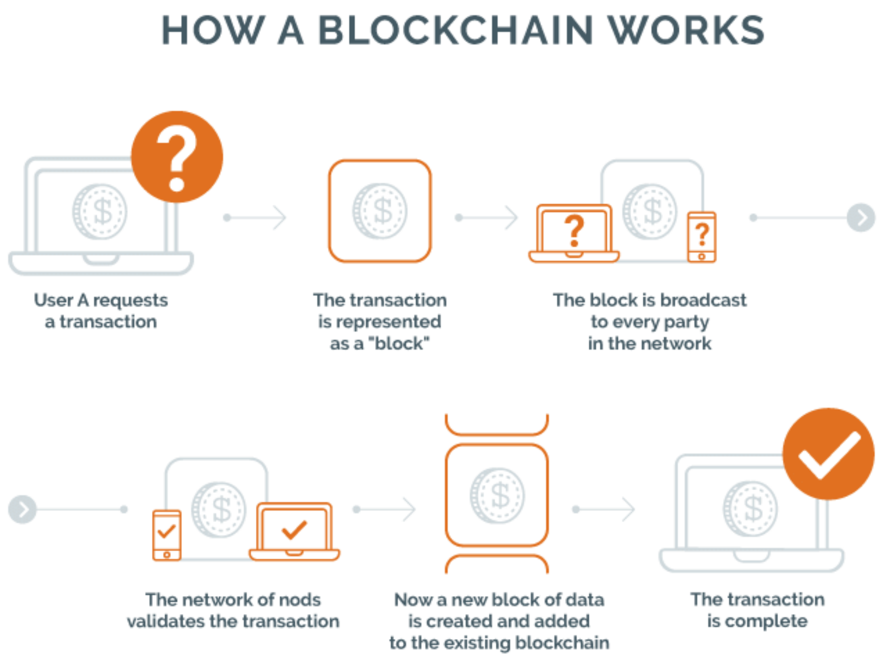

Figure 2: How Blockchain Works
Source: "Bitcoin Economy: Cryptocurrency Ecosystem Analysis and Long-term Projections (Cooper, 2022)

III. Descriptive Statistics of the Variables

Among the notable cryptocurrencies in the market, for the purpose of this dissertation, the following cryptocurrencies, plus the CCi30 index, were selected: Bitcoin, Ethereum, Binance, Ripple, Dogecoin, Stellar, Litecoin, and Monero. Exploring the specifics of each coin, it is essential to recognize the distinct roles they play within the broader cryptocurrency space, ranging from serving as digital currencies and stores of value to enabling smart contracts, cross-border transactions, and privacy-focused transactions. This diverse array of cryptocurrencies mirrors the evolution and diversification of blockchain applications and allows to navigate the complexities of this ever evolving and transformative financial landscape. Refer to Table 11 for more information.

Cryptocurrency	Overview	Comparison/Contrast
Bitcoin (BTC)	The first and most well-known cryptocurrency, Bitcoin serves as a decentralized digital currency and store of value.	Bitcoin is primarily a digital currency for peer-to-peer transactions and a store of value. It has a capped supply of 21 million coins, emphasizing scarcity.
Ethereum (ETH)	Ethereum is a decentralized platform enabling the creation of smart contracts and decentralized applications (DApps).	Ethereum goes beyond currency; it facilitates the creation of decentralized applications. Its use of smart contracts allows for more complex functionalities.
Binance (BNB)	Binance Coin is the native cryptocurrency of the Binance exchange, used to pay for transaction fees and participate in token sales on the platform.	Unlike Bitcoin and Ethereum, Binance Coin is tied to a specific exchange. It is primarily used for transaction fee discounts and participation in Binance-related activities.
Ripple (XRP)	Ripple aims to facilitate fast, low-cost international money transfers and is often associated with financial institutions.	Ripple is designed for fast and efficient cross-border transactions, distinguishing it from the proof-of-work mechanisms of Bitcoin and Ethereum.
Dogecoin (DOGE)	Initially started as a meme, Dogecoin has gained popularity and serves as a peer-to-peer digital currency.	Dogecoin, while sharing some characteristics with Bitcoin, has a larger supply and lower individual value, making it more accessible for microtransactions.
Stellar (XLM)	Stellar is a blockchain platform designed to facilitate fast and low-cost cross-border payments and token issuance.	Similar to Ripple, Stellar focuses on efficient international transactions but with a broader emphasis on financial inclusion.
Litecoin (LTC)	Created as the "silver to Bitcoin's gold," Litecoin is a peer-to-peer cryptocurrency with faster block	Litecoin shares similarities with Bitcoin but has a faster block generation time and uses a different

	generation times.	hashing algorithm (Scrypt).
Monero (XMR)	Monero is a privacy-focused cryptocurrency, aiming to provide anonymous and untraceable transactions.	Monero's primary focus on privacy sets it apart, using advanced cryptographic techniques to ensure confidentiality.

Table 11: Cryptocurrencies comparison and contrasts

Self-Elaboration. Sources: (Bhosale & Mavale, 2018; Brito & Castillo, 2014; Chohan, 2017; Gibbs & Yordchim, 2014; Hinteregger & Haslhofer, 2019; Lokhava et al., 2019; Quasim et al., 2020; Tikhomirov et al., 2018; Wood, 2014)

In summary, while all these cryptocurrencies share the decentralized nature inherent to blockchain technology, they have different purposes and features, ranging from peer-to-peer transactions (Bitcoin, Litecoin) to smart contract platforms (Ethereum) and privacy-focused options (Monero). Understanding their, and other currencies in general, unique characteristics is crucial for both individual and institutional investors making informed investment decisions.