UNIVERSIDADE CATOLICA PORTUGUESA

Behavioural Finance

Was the crypto market significantly impacted by herding behaviour from 2019 to 2024?

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Was the crypto market significantly impacted by herding behaviour from 2019 to 2024?

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Resumo

Este estudo investiga o comportamento de rebanho no mercado de criptomoedas entre 1 de janeiro de 2019 e 1 de janeiro de 2024, analisando cinco grandes criptomoedas e um índice. As conclusões revelam que embora exista uma ligação direta fraca entre os retornos lineares do mercado e a dispersão dos retornos, fatores não lineares significativos sugerem que os investidores nestes mercados tendem a tomar decisões diversas e autónomas, em vez de se juntarem. Isto questiona os entendimentos tradicionais do comportamento dos investidores em mercados voláteis como o das criptomoedas, sublinhando a importância de considerar factores não lineares como as influências psicológicas, as condições específicas do mercado e o impacto de eventos externos como a pandemia de COVID-19 na análise da dinâmica do mercado.

As conclusões têm implicações importantes para várias partes interessadas. Os legisladores podem conceber melhor a regulamentação para reforçar a estabilidade do mercado. Os investidores podem aperfeiçoar as suas estratégias com uma melhor compreensão da dinâmica do mercado. Além disso, os criadores de criptomoedas podem avaliar melhor o sentimento do mercado, permitindo inovações mais informadas.

Palavras-chave: Finanças comportamentais, Comportamento de rebanho, Criptomoeda, Volatilidade dos preços

Abstract

This study investigates herding behaviour in the cryptocurrency market between January 1, 2019, and January 1, 2024, analysing five major cryptocurrencies and an index. The findings reveal a nuanced relationship: while a weak direct link exists between linear market returns and return dispersion, significant non-linear factors suggest investors in these markets tend to make diverse and autonomous decisions rather than herd. This challenges traditional understandings of investor behaviour in volatile markets like cryptocurrencies, underscoring the importance of considering non-linear factors such as psychological influences, market-specific conditions, and the impact of external events like the COVID-19 pandemic in analysing market dynamics.

The findings have important implications for various stakeholders. Policymakers can better design regulations to enhance market stability. Investors can refine their strategies with a better understanding of market dynamics. Additionally, cryptocurrency developers can better judge market sentiment, enabling more informed innovations.

Keywords: Behavioural Finance, Herding Behaviour, Cryptocurrency, Price Volatility

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Chapter 1
Introduction

1.1 General Background

The Efficient Market Hypothesis (EMH) asserts that asset prices reflect all available information, making consistent market outperformance through stock picking or market timing impossible (Fama, 1970). However, the theory has faced scrutiny during financial crises and market bubbles, with critics highlighting its assumptions of perfect information and rationality as unrealistic (Grossman and Stiglitz, 1980). Instances like the dot-com bubble and the global financial crisis have challenged the EMH's ability to explain market behaviour (Shiller, 2000; Ball, 2009).

This critique has spurred the growth of behavioural finance, which acknowledges that investors are influenced by psychological biases and emotions rather than always acting rationally (Sharma and Kumar, 2019). Rejecting the Homo Economicus theory, behavioural finance recognizes behaviours like herding, where investors follow others rather than making independent decisions (Thaler and Mullainathan, 2000; Shefrin and Statman, 2011; Pompian, 2012; Barberis, 2017). Herding behaviour, a well-studied phenomenon in behavioural finance, can amplify market trends, leading to bubbles and crashes (Bikhchandani et al., 1992; Welch, 2000; Hirshleifer and Teoh, 2003; Chauhan et al., 2019).

During periods of market uncertainty or when investors face ambiguous information, herding behaviour becomes more pronounced (Hong and Stein, 1997). The presence of noise traders, who base decisions on non-fundamental factors, further exacerbates herding in markets (Devenow and Welch, 1996).

These dynamics are particularly significant in the emerging cryptocurrency market.

Recently, the manifestation of herding behaviour during the COVID-19 pandemic has been a significant area of interest. Heightened uncertainty and rapidly changing information during this period led many investors to closely follow market trends (Goodell, 2020; Zhang et al., 2020). This underscores the profound impact of global crises on investor psychology and market dynamics, emphasizing the importance of studying herding behaviour across various contexts (Albulescu, 2021).

The dynamics of the emerging cryptocurrency market are distinct from traditional financial markets. Cryptocurrency trading operates 24/7, attracting a diverse global participant base, including retail and institutional investors, traders, and speculators (Cheah and Fry, 2015). This decentralized market, lacking a central authority, faces challenges in security, regulation, and trust (Narayanan et al., 2016).

Cryptocurrencies are known for their high volatility, driven by technological advancements, regulatory developments, macroeconomic factors and market sentiment, which significantly influences price movements (Kristoufek, 2015). Stakeholders include individual investors, institutions, miners, traders, and market makers, all engaging in diverse strategies (Auer and Claessens, 2018).

Bitcoin holds a prominent position with the highest market capitalization and trading volume among digital assets (Coinmarketcap.com, 2024). Its market performance often mirrors the overall health of the market, closely watched by investors and analysts (Corbet et al., 2018). Beyond Bitcoin, other major cryptocurrencies such as Ethereum (ETH), Litecoin (LTC), Ripple (XRP), and Stellar Lumens (XLM) significantly influence the cryptocurrency landscape.

Ethereum is renowned for its smart contract capabilities, while Litecoin offers faster transaction confirmations. Ripple focuses on international money transfers, and Stellar Lumens targets unbanked populations. This diversity in cryptocurrencies not only enriches the market but also contributes to varying levels of investor behaviour and potential herding tendencies. Understanding these dynamics is crucial, as herding can amplify market trends, increase volatility, and contribute to speculative bubbles, making this an important field to further study and provide empirical evidence.

1.2 Research gaps

Herding behaviour in financial markets is a complex and multifaceted phenomenon, with various studies offering differing perspectives. Some scholars argue that herding becomes more pronounced during periods of market stress, indicating that investors tend to follow the actions of others during uncertain times, thereby amplifying market movements (Christie and Huang, 1995; Zhou and Lai, 2009). Conversely, another viewpoint suggests that herding behaviour may persist even in the absence of extreme market conditions, driven by social influence and cognitive biases (Hwang and Salmon, 2004). This divergence in findings highlights a significant research gap: it remains unclear whether herding behaviour is more dependent on market stress or if it is consistently present due to social and psychological factors (De Bondt, 1998; Chang et al., 2000).

Furthermore, there remains a notable gap in comprehending how different categories of institutional investors uniquely contribute to herding phenomena (Sias, 2004). Institutional investors are pivotal in exacerbating herding dynamics. Their large-scale transactions and propensity for herd-like behaviour can significantly amplify market movements and contribute to heightened volatility.

In the cryptocurrency market, behavioural studies are still in their infancy. Initial insights into herding behaviour in this context are provided, but further exploration into behavioural concepts, such as detecting herding behaviour and the fear of investors missing out on an opportunity, is needed (Nadarajah & Chu, 2017). Additionally, there is a call for a more systematic analysis of trading efficiency within the cryptocurrency market (Jalal, 2020). In examining cryptocurrency herding, different studies offer contrasting perspectives, with some focusing on the unique characteristics of digital assets while others emphasize broader market effects (Kaiser and Stöckl, 2020; Bouri et al., 2019).

However, there are warnings about the potential destabilizing effects of herding, underscoring the importance of addressing the associated risks, especially during periods of market volatility (Ajaz & Kumar, 2018). Additionally, despite these valuable contributions, significant gaps in understanding persist. Further research is needed to elucidate the underlying drivers of cryptocurrency herding, particularly in explaining why it occurs (Kallinterakis & Wang, 2019).

Additionally in recent times e emergence of the COVID-19 pandemic has introduced unprecedented levels of uncertainty and volatility into financial markets, including cryptocurrencies. Researchers indicate that the pandemic significantly altered investor behaviour and market dynamics (Sharif et al., 2020; Mandaci and Cagli, 2021). However, the specific impact of COVID-19 on herding behaviour in the cryptocurrency market remains underexplored. There is a critical need for empirical research to investigate whether and how the pandemic intensified herding tendencies among investors in digital assets.

1.3 Research Question

"Was the crypto market significantly impacted by herding behaviour from 2019 to 2024?"

Herding behaviour, where investors tend to follow the actions of others rather than conducting independent analysis, is widely recognized for its influence on market volatility and price fluctuations across financial markets (King and Koutmos, 2021; Omane-Adjepong et al., 2021; Papadamou et al., 2021). In cryptocurrency markets, characterized by their unique attributes like 24/7 trading and decentralized nature, understanding the role of herding is crucial. Despite its acknowledged impact, there remains a need for further empirical research to clarify whether herding intensifies during periods of market stress or persists due to inherent social and psychological factors (De Bondt, 1998; Chang et al., 2000).

Moreover, the unprecedented volatility introduced by the COVID-19 pandemic has significantly altered investor behaviour and market dynamics, including in cryptocurrencies. However, the specific impact of COVID-19 on herding behaviour within the cryptocurrency market remains inadequately explored (Sharif et al., 2020; Mandaci and Cagli, 2021). Addressing these gaps is essential as herding not only amplifies market trends but also exacerbates volatility and contributes to the formation of speculative bubbles.

1.4 Originality

This research brings originality through the examination of herding behaviour in the cryptocurrency market during a unique period from 2019 to 2024, which includes the COVID-19 pandemic. While herding behaviour has been studied extensively in traditional financial markets during crises, there remains a notable gap in empirical research specifically focused on herding dynamics within the cryptocurrency market during global crises (Mandaci and Cagli, 2021; Sharif et al., 2020).

1.5 Contribution to knowledge

This research contributes to the understanding of the complex dynamics between human behaviour and the cryptocurrency market, offering insights into its high volatility and sophisticated behavioural patterns (Kumar and Goyat, 2016; Bouri et al., 2019) by providing further empirical evidence in a more recent data frame.

This understanding is crucial for stakeholders present in this market such as individual and institutional investors, policymakers and regulators, and developers and innovators of the cryptocurrencies. Policymakers and regulators can benefit from this study to create new and better policies to enhance market stability, addressing concerns of market fragility and instability due to herding behaviour (Bhidé, 2010; Li et al., 2017; Chen et al., 2021). Individual and institutional investors gain insights for better trading strategies, as herding behaviour in the cryptocurrency market correlates with uncertainty in traditional financial markets, aiding in informed investment decisions (Goel and Dev, 2021). Developers and innovators of digital currencies can use the findings to better grasp market sentiment and speculative behaviour, opting to take more informed and cautious decisions regarding their own cryptocurrencies (Shen, 2022).

1.6 Next Chapters

The upcoming chapters are structured as follows: Chapter 2 reviews market efficiency, behavioural finance, and herding behaviour in the cryptocurrency market. Chapter 3 covers data sources and methodologies, while Chapter 4 presents empirical findings. Finally, Chapter 5 consolidates conclusions from the literature review and empirical tests, proposing future research directions.

Chapter 2
Literature Review

2.1 Herding Behaviour in Finance

In exploring herding behaviour, various disciplines offer distinct conceptualizations. In psychology, herding is often framed as the "bandwagon effect," where individuals adopt behaviours or beliefs simply because others do, regardless of personal conviction (DiMaggio, 1997). Sociology examines herding through the lens of collective behaviour, emphasizing how large groups synchronize their actions in response to stimuli or events (Turner & Killian, 1957). In ecology and animal behaviour, herding manifests as "flocking" or "swarming," where animals move collectively for protection, foraging, or migration purposes (Sumpter, 2010). Political science views herding as political bandwagoning, where voters align with popular candidates under the belief of winning (Berelson et al., 1954). Technology adoption and innovation studies observe herding in the adoption of new technologies based on others' decisions (Rogers, 1962). Economics and behavioural economics provide frameworks for analysing herding behaviour in financial markets. These discipline study how information dissemination and the rationality (or irrationality) of decision-making influence market participants' actions. They examine concepts such as "informational cascades" and "rational herding." Informational cascades occur when individuals base decisions on others' actions, assuming superior information, while rational herding posits following others due to perceived information advantages (Bikhchandani et al., 1992; Banerjee, 1992).

Among these diverse perspectives, the economic and behavioural economics framework provides a structured approach to studying herding behaviour in financial markets. This perspective is particularly relevant for analysing the dynamics of herding behaviour in the cryptocurrency market, where market sentiment and informational flows play crucial roles in influencing investor decisions and market outcomes.

2.2 Efficient Market Hypothesis

Financial history has witnessed a significant evolution, particularly with the integration of economic principles into market analysis. In 1944, new concepts like the "Economic Man-Statistical Man" emerged, representing individuals who meticulously analysed decisions based on statistical analysis, especially crucial in uncertain environments (Neuman, 1944). These developments laid the groundwork for rational investors operating in financial markets with an understanding of price randomness (Samuelson, 1965), leading to the formulation of the Efficient Market Hypothesis (EMH) (Fama, 1965). This EMH was later modified, categorizing market efficiency into three forms: weak, semi-strong, and strong (Fama, 1970).

2.2.1 Types of Market efficiency

In the weak form, asset prices reflect historical data like past prices and trading volume, making technical analysis ineffective for predicting future prices. Moving to the semi-strong form, asset prices incorporate all publicly available information such as financial statements and news releases. Thus, neither technical nor fundamental analysis consistently beats the market as all relevant public information is already priced in. Lastly, the strong form suggests that asset prices reflect both public and private information, including insider knowledge. However, even insider information fails to provide an advantage since market prices already reflect all available information, preventing new information from generating higher returns.

2.2.2 Critics of EMH

The Efficient Market Hypothesis (EMH) provides a framework for interpreting market behaviour, however real-world observations frequently challenge its assumptions. Studies have identified discrepancies between stock market performance and EMH predictions (Bondt & Thaler, 1985), suggesting that past performance may not reliably predict future outcomes. Anomalies such as the "January effect," where stock prices fluctuate predictably based on the time of year (Haugen and Lakonishok, 1988), and the size effect, where small-company stocks outperform large-company stocks (Keim, 1983), challenge EMH assumptions.

Additionally, the value investing model, favouring stocks with lower earnings-price ratios (Kahneman and Riepe, 1998), and excess volatility in stock prices (Shiller, 2003) further undermine EMH's efficiency. Market events like the 1987 stock market crash ("Black Monday") and the dot-com bubble of the late 1990s (Miller, 1991; Shiller, 2000), as well as the 2008 financial crisis (Lorenzoni, 2008), highlight systemic risks and inefficiencies not accounted for by EMH.

While EMH provides a theoretical foundation, real market dynamics often diverge due to complexities in investor behaviour and emotional influences on market prices (Grossman and Stiglitz, 1980).

2.3 Behavioural Finance

Behavioural Finance, rooted in human behavioural psychology, has emerged to explore psychological biases and irrational judgments that contribute to market inefficiencies (Thaler and Mullainathan, 2000). This interdisciplinary field integrates psychological insights with financial models to enhance understanding of financial markets, considering that market participants are not always fully rational (Jensen, 1978; Shleifer, 2000; Subrahmanyam, 2007).

Psychological studies have shown that individuals often misjudge probabilities and exhibit biases contrary to the axioms of utility theory (Stanovich, 1998). Further research also highlighted that individuals, including investors, tend to rely on simplified heuristics when making complex decisions, leading to systematic errors (Tversky & Kahneman, 1973). However, this approach is not yet widely integrated into traditional financial models, which predict minimal trading. Despite this, daily trading volumes exceed these predictions, leading to heightened volatility in stock prices (Shiller, 1984). Rational models also struggle to explain phenomena like companies paying cash dividends despite higher tax rates and stock prices rising post-dividend announcements (Modigliani and Miller, 1958; Mehra and Prescott, 1985).

While EMH once viewed returns as unpredictable, recent insights reveal partial predictability due to factors like mispricing or asset risk (Lakonishok et al., 1994). Moreover, technological advancements, particularly social media, amplify behavioural anomalies. Social media platforms can mobilize crowds globally, leading to herding behaviour where investors follow the crowd without thorough analysis (Raafat et al., 2009), posing new risks to market efficiency.

2.3.1 Limitations and Cognitive psychology

Behavioural finance has two fundamental pillars: limits to arbitrage and cognitive psychology.

The first pillar is backed by theoretical studies showing that in markets where both rational and irrational traders participate, irrational behaviour can significantly and persistently influence prices. The limitations on arbitrage can be seen as the costs faced by arbitrageurs, preventing them from correcting mispricings. This failure to correct mispricings leads prices to deviate further from their true, fundamental values (Jensen, 1978). Arbitrageurs often choose not to exploit these opportunities due to the impact of non-fundamental demand shocks on prices, rendering arbitrage less effective (Ritter, 2003). Additionally, research that studies the efficiency of prices and the CAPM highlights that the fundamental values of companies, such as their capital, equipment, inventories, and profits, do not fluctuate as rapidly or widely as stock prices (Morgenstern, 1970). This discrepancy suggests that markets may not always efficiently price assets.

The second pillar, cognitive psychology, sheds light on the biases and heuristics that influence investors' decision-making processes. Empirical evidence by cognitive psychologists reveals that these biases lead to suboptimal investment decisions and market irrationalities (Barberis and Thaler, 2003). These biases can be divided into three main categories: Self-deceptions, heuristic simplifications and social interactions.

Category	Biases	Concept
Self-Deception	Confirmation Bias	Investors seek information that confirms their existing beliefs, leaving them vulnerable to surprises. (Costa et. al., 2017)
	Hindsight Bias	Investors wrongly believe they could have predicted past events, leading to overconfidence. (Leković, 2020)
	Overconfidence	Investors often believe they are better than average, leading to risky investments in familiar assets. (Costa et. al., 2017)
	Overreaction	Investors tend to overreact to market news, leading to loser portfolios outperforming winner portfolios, challenging market efficiency. (Jensen, 1978; Subrahmanyam, 2007)
	Regret Theory	Investors may avoid good investments due to fear of regret over potential losses. (Loomes, 1982, 1987)
Heuristic Simplification	Anchoring	Investors may anchor on past information, leading to under or overreaction to new data. (Czerwonka, 2017)
	Framing	How information is presented can influence investor decisions, like presenting survival rate vs. mortality rate. (Özen & Ersoy, 2019)
	Prospect Theory	People become less risk-averse when expecting gains, but more risk-averse when expecting losses. (Tversky, 1979; Tversky and Kahneman, 1986; Tversky, 1992)
	Representativeness	Investors rely too heavily on recent experiences, assuming future patterns will resemble the past. (Rehan & Umer, 2017)
Social Interaction	Contagion effect	Market shocks in one region can spread globally, influencing local markets. Pure contagion challenges market efficiency. (Kaminsky, 2000; Edwards, 1999)
	Informational Cascades	Investors ignore private information and follow market trends, replicating actions of others. (Banerjee, 1992; Bikhchandani, 1992; Graham, 1999)
	Herding behaviour	Investors mimic others' actions, following the crowd instead of individual analysis. (Borensztein, 2003)

Table 1: Cognitive biases

Within the category of self-deception, confirmation bias emerges as a pervasive challenge for investors. Investors may overlook potential risks or alternative viewpoints, distorting their perception of reality and contributing to market inefficiencies (Costa et al., 2017). Another significant self-deception bias is hindsight bias, where investors believe they could have predicted past events. This can lead to overconfidence and an inflated sense of skill, resulting in riskier investment choices (Leković, 2020).

In the category of heuristic simplification, anchoring bias significantly influences investor behaviour by causing individuals to fixate on specific information or reference points when making decisions. By anchoring their judgments to arbitrary factors, investors may overvalue or undervalue assets, leading to suboptimal investment outcomes and distorting market prices (Czerwonka, 2017). Framing bias is another heuristic that affects decision-making. The way information is presented can heavily influence investor choices, such as the difference in decision-making when outcomes are framed in terms of potential gains versus potential losses (Özen & Ersoy, 2019). Additionally, overconfidence bias is a critical factor in heuristic simplification. Investors often believe they are better than average, leading to excessive trading and risk-taking, which can result in substantial financial losses and market volatility (Costa et al., 2017).

Regarding the category of social interactions, informational cascades, where investors disregard their private information and blindly follow the crowd, can lead to market irregularities and crashes (Banerjee, 1992; Bikhchandani et al., 1992; Hwang and Salmon, 2004). Another bias closely associated is herding behaviour. Herding behaviour involves investors imitating others, following the crowd rather than conducting independent analysis (Borensztein, 2003) reinforcing market trends and induces correlated trading activities, impacting asset prices regardless of their intrinsic value.

Despite its contributions to understanding market anomalies and investor behaviour, behavioural finance has faced several critiques. Critics argue that while behavioural finance highlights the irrational aspects of investor behaviour, it may underestimate the role of rational decision-making processes that also drive market dynamics (Rubinstein, 2000). Furthermore, the empirical evidence supporting behavioural biases is sometimes questioned due to methodological limitations, such as small sample sizes or data mining issues (Lo, 2004).

2.4 Herding Behaviour

Herding behaviour is an omnipresent phenomenon in financial markets. This phenomenon is the consequence of the herd instinct that makes the investors follow the crowd, not taking into account the individual cost effectiveness of an investment. This is the activity that builds up the market structure, determines the direction in which the market moves, the price movements and stability of the market.

In the study of herding behaviour within financial markets, researchers often categorize it into two distinct classifications: Rational vs Irrational.

2.4.1 Rational vs Irrational Herding

In the field of herding behaviour, a fundamental distinction arises between rational and irrational herding, each with distinct characteristics and implications for market dynamics. Rational herding, rooted in the desire to maximize returns and minimize risks, occurs when investors follow market trends based on rational assessments of available information and market conditions. This behaviour is often observed in well-informed and efficient markets, where investors perceive others' actions as signals of rational decision-making (Patni et al., 2014).

On the contrary, irrational herding involves following the crowd without thorough analysis, driven by emotions, social pressures, or cognitive biases rather than objective evaluation of market fundamentals. It tends to occur during periods of market uncertainty, heightened emotion, or speculation, when investors succumb to cognitive biases and social pressures (Wang, 1993).

Empirical research offers valuable insights into the prevalence and consequences of both types of herding behaviour. Studies examining rational herding often focus on situations where investors observe others' actions and perceive them as informative signals of underlying market conditions or investment opportunities (Devenow and Welch, 1996). In contrast, irrational herding has been extensively studied in the context of behavioural finance, which highlights the role of psychological biases and social influences in shaping investor behaviour (Bikhchandani and Sharma, 2001).

2.4.2 Spurious vs Intentional Herding

Inside the rational herding we can define the behaviour in two categories, spurious or intentional herding.

Spurious Herding happens when investors show a tendency to act in a synchronized manner despite the absence of a deliberate intention and due to external factors that are common for all the investors, also known as the relative homogeneity, which implies similarities in the background of the investors coming from the same educational levels, work experience and regulatory environments (De Bondt, 1997; Voronkova, 2005). Spurious herding is one of the practical manifestations that will occur in the equity market when interest rates all of a sudden go up and it becomes unattractive for investors to buy stocks.

Intentional Herding occurs when investors deliberately follow others due to rational or psychological reasons. Conformity plays a significant role in this behaviour, as it makes it easier for individuals to mimic others (Hirshleifer, 2001 Bikhchandani and Sharma, 2001). Additionally, investors may follow others when they believe those individuals possess superior information or better information processing skills (Shiller, 1995; Bikhchandani et al., 1992). Another psychological factor driving intentional herding is reputation. Financial professionals are often evaluated by their peers, leading underperformers to imitate better-performing colleagues to 'free-ride' on their success (Scharfstein, 1990; Trueman, 1994). Conversely, successful individuals may follow the crowd to avoid the risk of failure, even if it means missing out on rational choices (Graham, 1999).

Distinguishing spurious from intentional herding is a complex task full of challenges. Therefore, the models that study herding behaviour opt to study the rational behaviour as a whole providing more results in empirical researches.

2.5 Empirical evidence on Herding Behaviour

Herding behaviour in financial markets has been extensively studied to understand its motives, impacts on market stability, and the cognitive biases underlying it. Early research identified key psychological biases such as herd mentality and loss aversion, which significantly influence investor decision-making. Studies emphasized that herd mentality often leads to exaggerated price swings, driven by investors' tendency to follow prevailing market trends rather than conducting independent analysis (Shiller, 1984). Additionally, further research explored how loss aversion motivates investors to herd during periods of perceived risk, amplifying market volatility (De Long et al., 1990).

Studies examining herding among institutional investors have revealed its prevalence beyond retail traders. Institutions, as major market players, exhibit similar herding behaviours, contributing to short-term market distortions

(Friedman, 1984), tending to correct as market fundamentals reassert themselves over time (Lakonishok et al., 1992) indicating that while institutional herding can exacerbate volatility temporarily, it does not necessarily dictate long-term market outcomes. Further findings also highlighted that during periods of heightened market uncertainty, intra-horizon spillovers increase significantly (Sharif et al., 2020).

During financial crises, herding behaviour intensifies due to increased complexity and uncertainty. Research shows heightened herding during stressed market conditions (Hirshleifer and Teoh, 2003; Demirer et al., 2010; BenSaïda, 2017; Deng et al., 2018). This pattern reflects how market sentiment, influenced by speculative motives, amplifies perceptions of risk across asset classes such as bonds and commodities (Cai et al., 2019; Cakan et al., 2019). More recent research show that during COVID-19 pandemic, herding behaviour among investors tends to intensify due to heightened uncertainty and market complexity (Chang et al., 2020; Wu et al., 2020). The emergence of the COVID-19 pandemic introduced unprecedented uncertainty and volatility into financial markets, including cryptocurrencies. This global crisis significantly impacted investor behaviour and market dynamics highlighting the synchronization in trading decisions and increased market volatility among cryptocurrency investors during crisis periods (Mandaci & Cagli, 2021).

2.5.1 Significant Herding Behaviour in Cryptocurrency markets

The emergence of cryptocurrency markets provides a unique context for studying herding behaviour, characterized by high volatility and a lack of traditional regulation.

Research suggests that herding behaviour is observable in cryptocurrency markets, particularly during periods of high uncertainty and rapid price movements (Ajaz and Kumar, 2018), observing that during times of market turbulence, investors tend to follow the actions of larger players, creating herding effects. This behaviour is often driven by a fear of missing out (FOMO) on potential gains or losses (Amirat and Alwafi, 2020). Additionally, evidence was found supporting the presence of herding behaviour in cryptocurrency markets, especially among retail investors (Ballis and Drakos, 2020). This indicates that retail investors, lacking access to sophisticated analytical tools, are more likely to follow the actions of larger institutional investors, leading to herding tendencies.

Further exploration identified distinct patterns of collective behaviour among cryptocurrency investors, suggesting that herding behaviour can lead to market inefficiencies and increased volatility, particularly when investors react to market movements instead of fundamental information (Bouri et al., 2019).

Complementing previous research, further research also delved into the interdependency and asymmetries of herding behaviour in cryptocurrency markets finding that during periods of heightened market uncertainty, herding tends to intensify as investors seek safety in following the crowd (Jalal et al., 2020).

2.5.2 Non-Significant Herding Behaviour in Cryptocurrency markets

However, research has also suggested limited evidence of significant herding behaviour in cryptocurrency markets. Investors in these markets tend to act autonomously rather than conform to collective sentiment, indicating a lack of strong herding tendencies (Poyser, 2018; Bouri et al., 2019) and). Additionally, herding behaviour was less prevalent in the Chinese cryptocurrency market, particularly during periods of market stress (Kallinterakis and Wang, 2019). Moreover, studies focusing on specific cryptocurrencies, such as Bitcoin, have also indicated minimal impact from herding behaviour. Herding behaviour is not a significant driver of prices in the Bitcoin market, as investors often act independently based on their private information (Kristoufek, 2013). Similarly, the subdued nature of herding behaviour in Bitcoin markets suggests that investors make decisions autonomously (Li et al., 2017).

These studies collectively contribute to our understanding of how herding behaviour manifests in the dynamic and volatile world of cryptocurrencies.

2.6 Macroeconomic Context – 2019 to 2024

The period from 2019 to 2024 witnessed significant transformations in the global economy, shaped by various macroeconomic factors, geopolitical events, and the rise of cryptocurrencies.

Global GDP experienced fluctuations during this time. While 2019 projected stability with modest growth at 2.9%, the eruption of the COVID-19 pandemic in 2020 led to a sharp contraction, resulting in a -3.5% decline in global GDP growth. Despite subsequent signs of recovery, challenges such as rising inflation and uneven growth persisted across regions.

Inflation dynamics played a crucial role in shaping economic policies. The pandemic-induced disruptions in 2020 initially led to deflationary pressures, followed by concerns about rising inflation as economies reopened and stimulus measures were implemented. Central banks responded with accommodative monetary policies to support economic recovery while closely monitoring inflationary risks.

Geopolitical tensions, including trade disputes, regional conflicts, and geopolitical rivalries, contributed to market uncertainties. Events such as the U.S.-China trade war, Brexit negotiations, and conflicts in the Middle East impacted global trade and investment flows, influencing investor sentiment and market dynamics (Eurasia Group, 2022).

The COVID-19 pandemic emerged as a defining event, causing widespread disruptions to economies and societies worldwide. Lockdowns, supply chain disruptions, and travel restrictions led to sharp contractions in economic activities, triggering recessions in many countries (World Bank, 2020). Governments responded with unprecedented fiscal stimulus packages and monetary easing measures to mitigate the economic fallout and support recovery efforts.

Financial markets experienced heightened volatility, reflecting uncertainties surrounding the pandemic, geopolitical developments, and shifts in investor sentiment. Traditional assets like stocks and bonds faced turbulent periods, with major indices experiencing significant fluctuations. Amidst this volatility, the cryptocurrency market emerged as a notable player, attracting growing interest from investors and institutions.

The cryptocurrency market operates as a decentralized financial system where digital assets are traded securely using blockchain technology. Demand for cryptocurrencies stems from speculative investment, hedging against traditional currency instability, and their potential utility in decentralized applications. Supply is controlled by cryptographic protocols that define the creation and availability of each cryptocurrency, influencing market dynamics (Nakamoto, 2008). Security in the cryptocurrency market is a critical concern, given its vulnerability to cybercrime and hacking incidents (Moore & Christin, 2013). Cryptographic techniques protect transactions and user identities against theft and fraud attempts in this digital landscape. Furthermore, market concentration is notable, with a few major cryptocurrencies dominating in terms of market capitalization and trading volumes, such as Bitcoin and Ethereum. Overall, the cryptocurrency market represents a transformative aspect of finance, characterized by its decentralized structure and technological innovations.

Regulatory approaches to cryptocurrencies varied across jurisdictions. While some countries embraced cryptocurrencies, offering clear regulatory frameworks to foster innovation, others remained cautious due to concerns surrounding investor protection, money laundering, and financial stability. Regulatory initiatives such as the SEC's crackdown on unregistered securities offerings and China's strict bans on cryptocurrency trading and mining shaped market dynamics and investor behaviour.

The cryptocurrency market experienced exponential growth during this period. Total market capitalization surged from around $200 billion in 2019 to over $2 trillion by 2023 (Coinmarketcap.com, 2024). Bitcoin, the pioneering cryptocurrency, maintained its position as the dominant digital asset but saw its market dominance fluctuate. Despite this the cryptocurrency market features a diverse array of major coins, each with distinct roles and impacts. Ethereum (ETH) stands out for its smart contract capabilities, enabling decentralized applications and protocols. Litecoin (LTC) facilitates faster transaction confirmations, catering to everyday transaction needs. Ripple (XRP) specializes in efficient international money transfers, while Stellar Lumens (XLM) focuses on providing financial services to the unbanked. Altcoins also gained traction, contributing to market diversification and innovation.

Market participants within the cryptocurrency space showcased a diverse spectrum. Retail investors, including individuals and small traders, continued to play a significant role, facilitated by platforms like Robinhood and Coinbase. Cryptocurrency mining operations became more decentralized, aiming to enhance network security and resilience.

2.7 Hypothesis

H1: Herding Behaviour was significantly present in the Cryptocurrencies Market from 2019 to 2024

During periods of financial crises and heightened uncertainty, research consistently shows an intensification of herding behaviour, amplifying market fluctuations (Hirshleifer and Teoh, 2003; Demirer et al., 2010; BenSaïda, 2017; Deng et al., 2018). Additionally, recent examinations during the COVID-19 pandemic further affirm increased herding behaviour among cryptocurrency investors, driven by market complexity and uncertainty (Chang et al., 2020; Wu et al., 2020; Mandaci & Cagli, 2021).

Moreover, empirical findings reveal observable patterns of herding behaviour in cryptocurrency markets, particularly during periods of rapid price movements and market turbulence (Ajaz and Kumar, 2018; Ballis and Drakos, 2020). Despite some studies indicating variability in the prevalence of herding behaviour across different cryptocurrencies and market conditions (Poyser, 2018; Bouri et al., 2019; Kallinterakis and Wang, 2019; Kristoufek, 2013; Li et al., 2017), the cumulative evidence supports the hypothesis that herding behaviour was notably present in the cryptocurrency market.

Studying the presented hypothesis will provide further empirical evidence on a more recent data frame of the presence or not of herding behaviour in the cryptocurrency market.

Chapter 3
Data and Methodology

3.1 Qualitative vs Quantitative approach

In the field of research methodologies, the debate between qualitative and quantitative approaches has long been a topic of discussion. Qualitative methods, such as interviews and case studies, offer a deep and comprehensive exploration of subjects, providing insights into their motives and emotions. These methods are particularly valuable in establishing the motives and feelings of the subjects (Heyink and Tymstra, 1993). Additionally, they provide a deeper contextual comprehension and insights on subjective experiences (Seers, 2011).

On the other hand, quantitative methods excel in measuring trends and relationships with precision. Quantitative modelling, as showcased in their work on financial market forecasting (Thimmaraya and Masuna, 2011), demonstrate the effectiveness of mathematical models in predicting market behaviour being instrumental in explaining market dynamics.

For this study the quantitative approach is the most suited. This method allows precise examination of cryptocurrency data and able to handle the numerical complexities of this data, enabling us to extract meaningful insights and test hypotheses about market behaviour (Javaira and Hassan, 2015).

3.2 Data collected

The study period is a five-year time frame, from January 1, 2019, to January 1, 2024, containing a total of 1826 days.

The data in this study is derived from secondary data that is in the form of panel data containing the daily closing prices of five cryptocurrencies and the CCi30 as a benchmark for overall cryptocurrencies market behaviour. The main currencies in our analysis are Bitcoin (BTC), Ethereum (ETH), Litecoin (LTC), Ripple (XRP), and Stellar Lumens (XLM).

The cryptos were picked based on their market capitalization and the level of recognition. BTC alone represents over 40% of the total cryptocurrency market capitalization (Coinmarketcap.com, 2024). ETH, with a market cap exceeding $400 billion, is known for its smart contract capabilities (Coinmarketcap.com, 2024). LTC, valued at over $8 billion, offers quicker transaction confirmations (Coinmarketcap.com, 2024). XRP, with a market cap exceeding $22 billion, focuses on international money transfers (Coinmarketcap.com, 2024). XLM, valued at over $6 billion, targets unbanked populations (Coinmarketcap.com, 2024). This diverse selection enables a comprehensive analysis of varying market caps, trading volumes, and technological features.

The CCi30, capturing the top 30 capitalized coins, serves as a crucial benchmark for the cryptocurrency market. It employs a weighting technique based on factors like market capitalization and trading volume, assigning weights to assets according to the square root of their market capitalizations.

The daily closing prices of the cryptocurrencies were taken from the Coinmarketcap website. The CCi30 was obtained directly from their official website.

The dataset has suffered no manipulations and contains anomalies, which are worth analysing to confirm or not the herding behaviour as well as to account for the asymmetric reaction during bullish and bearish market movements (Chiang and Zheng, 2010).

The data reliability is a vital point in the study for its validity. Coinmarketcap and CCi30 are two well-known and trustworthy sources which are renowned for their correct and up-to-date financial information. These platforms have become the main tools of empirical research in the field of cryptocurrency analysis (Bouri et. al., 2019; Calderón, 2019).

3.3 Variables

For this research logarithmic returns were not used in this calculation because of the skewed distribution commonly observed in the cryptocurrency market. Furthermore, logarithmic returns are less accurate than simple returns, and risk and return calculations are not independent, with the latter being more important for short observation periods (Hudson and Gregoriou, 2010). Additionally, simple returns give a more direct indication of change in prices over the given period (Hudson, 2015).

This study will examine the daily returns of the previous presented data. The daily return is the percentage change in the closing price from one day to the next and is computed as follows:

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

CPt is the closing price day t and $CPt{-}1$ is the closing price the day before t.

3.4 Methodology

3.4.1 Cross sectional standard deviation (CSSD)

Quantitative models, such as the Cross-Sectional Standard Deviation (CSSD) (Christie and Huang, 1995), provide valuable insights into herding behaviour in financial markets. This model helps study return dispersion among portfolio assets.

The CSSD model identifies asymmetric behaviour during extreme market conditions. Negative coefficients indicate herding behaviour, where investors mimic each other, while positive coefficients suggest returns correlate with extreme market movements, indicating a lack of herding (Christie and Huang, 1995). However, a key limitation of the CSSD model is its assumption of a linear relationship between return dispersion and the market portfolio return. This assumption may lack robustness in the presence of outliers or extreme market scenarios (Patterson and Sharma, 2005; Tan et al., 2008). This limitation is especially relevant in volatile cryptocurrency markets.

Recognizing these limitations, another model was proposed, the Cross-Sectional Absolute Deviation (CSAD) model as an improved approach.

3.4.2 Cross-Sectional Absolute Deviation (CSAD)

From a CSAD perspective, understanding the dispersion of asset returns in comparison to market returns provides valuable insights into investor behaviours and market dynamics. The CSAD formula calculates the average absolute deviation of individual asset returns from the market portfolio return (Chang et al., 2000). This provides a quantifiable measure of how closely individual asset returns align with the broader market, indicating potential herding behaviour among investors and is first formula applied in this study's empirical test structure.

The CSAD model can be expressed as:

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

Where:

- CSADt: It measures the average absolute deviation of each asset's return from the return of the market portfolio.
- N: Total number of assets in the portfolio.
- |R_i,t - R_m,t|: Calculates the absolute difference between the return of each asset i at time t (denoted by Ri,t) and the return of the market portfolio at the same time t (denoted by Rm,t).

Integrating CSAD with the Capital Asset Pricing Model (CAPM) enhances its utility even further incorporating non-linear elements, enhancing its ability to capture deviations from market norms. Incorporating these non-linear elements into the CSAD model provides a nuanced understanding of how deviations from market norms intensify, offering insights into investor sentiment and potential market trends.

The second formula used in this study is to conduct an ordinary least square (OLS) regression of that CSAD integration with CAPM. OLS is often preferred over generalized least squares (GLS) in certain contexts due to its simplicity and ease of interpretation. While GLS can offer more efficient estimates in the presence of heteroscedasticity or autocorrelation, OLS remains robust and computationally straightforward, especially when the primary goal is to understand the general relationship between variables rather than address complex variance structures (Wooldridge, 2010). Moreover, in the context of high-frequency and highly volatile data like that of the cryptocurrency market, OLS's computational feasibility makes it a practical choice for initial explorations and large datasets (Gujarati & Porter, 2009).

This integration allows for a deeper exploration of how herding behaviour impacts cryptocurrency assets and can be expressed by the following expression:

$$CSADt = y_0 + \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 (R_{m,t})^2 + \epsilon_t$$

Where:

- α: Intercept term.
- $\gamma 1$: Captures the linear relationship between market return and return dispersion.
- $\gamma 2$: Captures the non-linear relationship, indicating deviations from market norms.
- $\gamma 3$: Reflects the influence of market return squared.
- |Rm,t|: Absolute value of the market return at time t.
- εt: Error term, accounting for unexplained variations in the model.

Despite this, the model still has some limitations. The cryptocurrency market is characterized by high volatility and rapid changes, which can affect the CSAD measure. Sudden price swings due to market news or regulatory changes can lead to significant deviations in returns, potentially obscuring true herding behaviour (Balcilar et al., 2013). Furthermore, the CSAD model assumes a homogeneous reaction among assets, which might not hold true for the diverse range of cryptocurrencies. Different cryptocurrencies have varying levels of adoption, liquidity, and investor bases, which can lead to different herding patterns that the model may not accurately capture (Lao & Singh, 2011).

3.5 Software

For the data analysis purposes, MS Excel was used which is a versatile tool allowing us to fulfil different tasks including statistics and data processing. Even though alternative statistical software packages such as R, Python, and MATLAB are accessible nowadays, the size of our study sample will not require a more sizable tool as Excel is quite capable and powerful to process the obtained results (Hossein, 2020).

Chapter 4
Results

4.1 Data characteristics

The comparison of the monthly returns over 5 years period (February 2019 through January 2024) between the five selected cryptocurrencies (BTC, ETH, LTC, XRP, XLM) and the CCi30 index reveals not only certain trends but also the times of volatility.

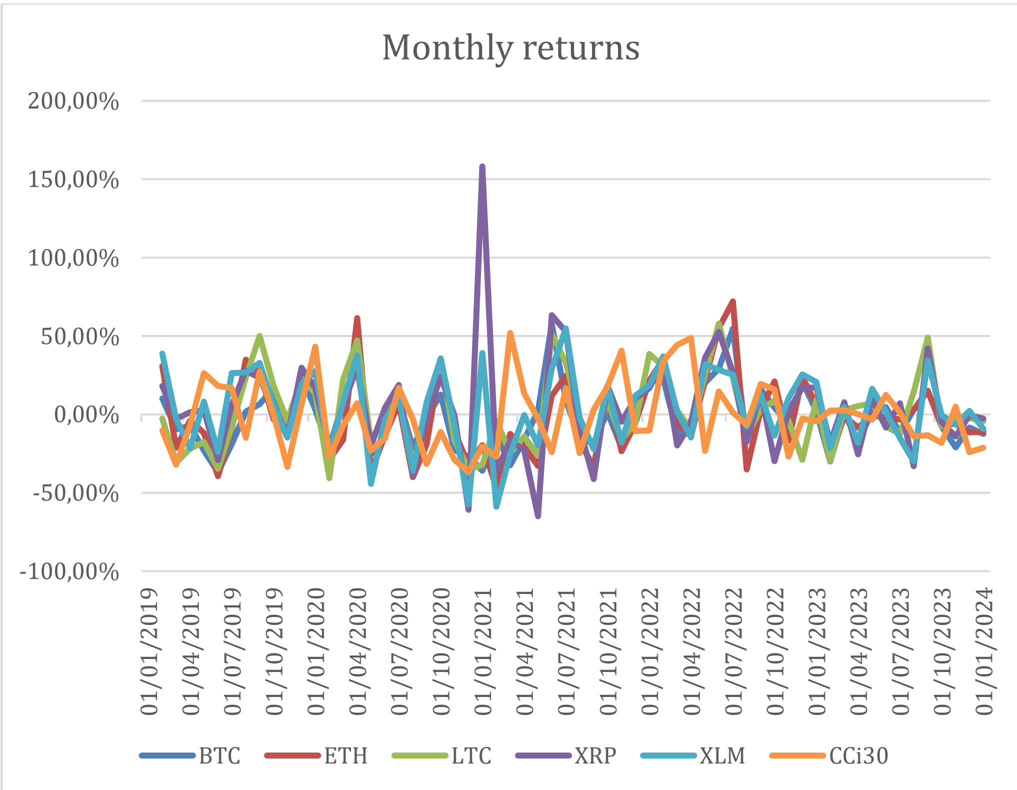

Figure 1: Evolution of Monthly returns

Notable spikes occurred periodically, aligning with historical volatility in the cryptocurrency market, including substantial price surges and corrections.

Out of the average monthly returns, XLM and XRP stand out as the most volatile compared to BTC, the leading cryptocurrency. XLM showed a maximum monthly return of 72.07% and a minimum return of -40.00%, while XRP had a maximum monthly return of 61.44% and a minimum return of -46.65%. These fluctuations are notably higher than BTC's range of returns, which ranged from a maximum of 57.63% to a minimum of -36.91%. The CCi30 market index, which serves as a wide market benchmark, has also witnessed substantial fluctuations ranging from a maximum of 48.71% to a minimum of -36.80%.

The above findings vividly demonstrate the volatility and dynamics of the cryptocurrency market where its variety of cryptocurrencies and CCi30 index may experience both consistently high and low turnovers over a chosen period.

Looking closer at the daily returns we can see further evidence of the market volatility.

Daily Returns	BTC	ETH	LTC	XRP	XLM	CCi30
Max	18,75%	25,95%	30,83%	73,08%	74,92%	21,61%
Min	-37,17%	-42,35%	-36,18%	-42,33%	-33,63%	-38,40%

Table 2: Data characteristics: Min & Max of the sample

The descriptive statistics of the daily returns is displayed the table below:

	BTC	ETH	LTC	XRP	XLM	CCi30
Mean	0,0019587	0,0025576	0,0016656	0,0017997	0,0014295	0,0018756
Median	0,0007550	0,0009255	0,0007842	-0,0000990	0,0003684	0,0033203
Min.	-0,3716954	-0,4234722	-0,3617733	-0,4233408	-0,3363182	-0,3839845
Max.	0,1874647	0,2594753	0,3082949	0,7307505	0,7492410	0,2161367
Std. Dev.	0,0349526	0,0445810	0,0487311	0,0562567	0,0538928	0,0393490
Skewness	-0,3878646	-0,3732520	-0,0347332	2,4129656	2,8462087	-0,8575682
Kurtosis	10,2424903	8,1100352	6,9227213	30,7213388	36,1909625	9,3052931

Table 3: Data characteristics: Descriptive statistics

All cryptocurrencies, except Bitcoin (BTC), exhibit positive skewness in their return distributions, indicating a concentration of extreme positive returns. Bitcoin shows a skewness close to zero, suggesting a more symmetric return distribution. BTC and Ethereum (ETH) have relatively stable mean returns, with BTC at 0.19587% and ETH at 0.25576%. XRP and Stellar Lumens (XLM) show significant positive skewness, with XLM having the highest skewness of 2.85, indicating frequent extreme positive returns.

Bitcoin exhibits a high kurtosis of 10.24, suggesting a distribution with a higher peak and heavier tails, indicating a higher probability of extreme returns. XRP and XLM have even higher kurtosis values of 30.72 and 36.19, respectively, indicating distributions with more outliers and a higher likelihood of extreme returns. The market proxy, CCi30, has a slightly negatively skewed distribution with a skewness of -0.86, indicating a concentration of extreme negative returns. Additionally, CCi30 exhibits a kurtosis of 9.31, suggesting fatter tails and a higher likelihood of extreme returns compared to a normal distribution.

Overall, this samples is well-suited for studying the behaviour of cryptocurrencies, capturing the nuances of individual asset distributions and the broader market trends.

4.2 Main results

To test the hypothesis the above formula (i) was applied followed by a verification of the robustness of the results through formula (ii). The extracted results are displayed in the following table:

	RET^2	ABS RET	RET	Intercept	R2 Adjusted
Coefficient	0,980952389	0,661167132	-0,025401822	0,024178	0,360164129
Standar Error	0,251481418	0,044334107	0,019206982	0,001162	
t-stat	3,900695324	14,913284	-1,322530616	20,80882	
p-value	9,93989E-05	1,52854E-47	0,186157501	1,87E-86	

Table 4: Main results

The regression analysis yielded an adjusted R-squared value of 0.360, indicating that approximately 36% of the variability in return dispersion is explained by the model. This suggests a moderate fit, which provides meaningful insights into the relationship between market returns and return dispersion.

The intercept term was significant with a coefficient of 0.024, a t-statistic of 20.809, and a p-value of 1.87E-86, indicating a base level of return dispersion not explained by the model variables.

The coefficient for the squared market return (RET^2) was 0.981 with a highly significant t-statistic of 3.901 and a p-value of 9.94E-05. This implies that as market returns increase non-linearly, the dispersion of individual asset returns also increases, suggesting a decrease in herding behaviour. The coefficient for the absolute market return (ABS RET) was 0.661, with an extremely significant t-statistic of 14.913 and a p-value of 1.53E-47. This means that greater absolute market returns correlate with higher return dispersion, further supporting the idea of reduced herding during high volatility. In contrast, the coefficient for the linear market return (RET) was -0.025, with a t-statistic of -1.323 and a p-value of 0.186, suggesting this relationship is not statistically significant.

4.3 Discussion

The study's main hypothesis proposed significant herding behaviour in the cryptocurrency market from 2019 to 2024. However, the regression analysis challenges this hypothesis. The model achieved an adjusted R-squared of 0.36, indicating that approximately 36% of return dispersion variability is explained. This suggests a moderate model fit, prompting nuanced insights into herding behaviour.

Notably, the analysis revealed significant findings: the squared market return (RET^2) coefficient was positively significant, indicating that non-linear increases in market returns correlate with higher return dispersion. Similarly, the absolute market return (ABS RET) coefficient showed a positive significance, suggesting that greater absolute market returns also lead to increased return dispersion. In contrast, the linear market return (RET) coefficient was not statistically significant.

These findings imply that during periods of high market returns or high volatility, investors tend to exhibit more varied and independent investment decisions, reducing the tendency to herd. This is contrary to the expectation that high volatility and market returns would lead to more pronounced herding behaviour. The findings are consistent with several studies that found limited evidence of herding in cryptocurrency markets, suggesting that investors often act independently rather than conform to collective sentiment (Poyser, 2018; Bouri et al., 2019). Moreover, studies also reported minimal herding impact on Bitcoin prices, indicating that even in highly volatile environments, cryptocurrency investors may rely more on individual analysis rather than following the crowd (Kristoufek, 2013; Ciaian et al., 2016). These findings are supported by the significant coefficients for squared and absolute market returns in our study, which show increased return dispersion, a sign of reduced herding.

Furthermore, during the COVID-19 pandemic, herding behaviour was observed to intensify in broader financial markets (Mandaci & Cagli, 2021; Chang et al., 2020), yet our study indicates that cryptocurrency markets may behave differently. This deviation can be due to the decentralized nature and diverse investor base of cryptocurrencies, which may lead to more individualized trading behaviour even in crises.

Chapter 5
Conclusion

5.1 Conclusions

This study represents a significant advancement in understanding herding behaviour within cryptocurrency markets, challenging prevailing hypotheses about its prevalence between 2019 and 2024.

Our study contributes to the literature by offering new insights into investor behaviour dynamics in cryptocurrency markets. The identification of a weak direct relationship between linear market returns and return dispersion, coupled with significant non-linear factors, suggests that investors in these markets tend to make diverse and autonomous investment decisions. This challenges conventional understandings of herding behaviour and underscores the complexity of investor decision-making processes.

Furthermore, this study emphasizes the importance of considering non-linear factors in analysing volatile markets like cryptocurrencies. By acknowledging the influence of psychological, market-specific, and external economic conditions, including the impact of the COVID-19 pandemic, the theoretical framework for understanding investor behaviour is enriched. The pandemic introduced unprecedented market volatility and uncertainty, further highlighting the necessity to include such external factors in herding behaviour analysis (Goodell & Goutte, 2021).

Moreover, while prior research primarily examines Bitcoin returns and herding behaviour (Kristoufek, 2013), our study expands this analysis to encompass a wider array of cryptocurrencies and a more extensive temporal scope. Through this broader approach, our research provides valuable insights into the dynamics of herding behaviour across diverse cryptocurrency assets. The significant coefficients for non-linear market return factors suggest that investor decision-making processes are complex and influenced by a variety of factors, beyond mere market returns (Bouri et al., 2019; Poyser, 2018).

5.2 Management Implications

The study provides actionable recommendations tailored to stakeholders in the cryptocurrency market, drawing insights from the research.

Policymakers and regulators can utilize the study's insights to shape educational initiatives to emphasize fundamental analysis and risk management, develop guidelines that encourage long-term investment strategies over speculative trading and implement regulations that mandate transparency in market operations and discourage excessive leverage, thereby promoting a stable and sustainable market environment (Bhidé, 2010; Li et al., 2017).

Complementing this, for individual and institutional investors, the study advocates for diversified portfolios grounded in rigorous fundamental analysis encouraging investors to allocate assets based on long-term growth potential than short-term market sentiment. Furthermore, providing educational resources on fundamental analysis techniques and risk assessment will empower investors in making more informed and rational decisions. (Chen et al., 2021).

Regarding cryptocurrency developers and innovators in the cryptocurrency space can leverage the study's findings to design platforms and products that cater to the needs of independent investors. By prioritizing transparency, accessibility, and education within their offerings, developers can empower users to make informed decisions based on their individual research and analysis, fostering a more robust and resilient market ecosystem (Shen, 2022).

5.3 Limitations

This study has several limitations that affect its findings and applicability. The cryptocurrency market's rapid evolution, high volatility, and continuous innovation make it challenging to maintain up-to-date datasets and perform comprehensive analyses. Data fragmentation and occasional unreliability complicate drawing robust conclusions. Additionally, the dynamic nature of regulatory policies and institutional responses adds significant uncertainty. Governments and financial institutions are still developing measures for cryptocurrencies, influencing market dynamics and making it difficult to capture a stable snapshot of herding behaviour.

Furthermore, human behaviour in financial markets is influenced by numerous psychological and social factors that are hard to quantify and model accurately. The statistical and econometric models used have inherent limitations and may not fully capture the diverse motivations and cognitive biases behind individual investment decisions. Lastly, the specific timeframe of 2019 to 2024 may limit the findings' applicability to different periods or regulatory environments, as observed patterns might not persist under future market conditions.

5.3 Future Research

Future research in cryptocurrency markets should expand to include a wider array of cryptocurrencies, especially those with lower market capitalization. Incorporating diverse digital assets will provide a more comprehensive understanding of market dynamics and investor behaviour across different cryptocurrency ecosystems, aiding in a nuanced analysis of factors influencing price movements and market sentiment.

Moreover, exploring innovative methodological approaches, such as advanced statistical techniques and machine learning integration, can enhance the study of herding behaviour and market dynamics. Techniques like longitudinal analyses can track changes in herding behaviour over time, assessing the impact of regulatory changes and technological advancements on market trends. Additionally, integrating machine learning can identify patterns and correlations in large datasets, contributing to a deeper comprehension of investor behaviour and market dynamics in cryptocurrency markets.

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Bibliography

1. Ajaz, T. & Kumar, A. 2018. Herding in Crypto-currency markets. Annals of Financial Economics. Vol. 13, No. 02, 1850006.
2. Albulescu, C. T. (2021). COVID-19 and the United States financial markets' volatility. Finance Research Letters, 38, 101699
3. Amirat, A., & Alwafi, W. 2020. Does herding behaviour exist in cryptocurrency market? Cogent Economics & Finance, 8: 1, 1735680.
4. Auer, R., & Claessens, S. (2018). Regulating cryptocurrencies: assessing market reactions.
5. Balcilar, M., Demirer, R., & Hammoudeh, S. (2013). Investor herds and regime-switching: Evidence from Gulf Arab stock markets. Journal of International Financial Markets, Institutions and Money, 23, 295-321.
6. Ball, R. (2009). The Global Financial Crisis and the Efficient Market Hypothesis: What Have We Learned?. Wiley-Blackwell: Journal of Applied Corporate Finance.
7. Ballis, A. & Drakos, K. 2020. Testing for herding in the cryptocurrency market. Finance Res. Lett., 33, p. 101210
8. Banerjee, V. 1992. "A Simple Model of Herd Behavior", The Quarterly Journal of Economics, Vol. CVII, 3: 797-817.
9. Barberis, N. & Thaler, R. 2003. "A Survey of Behavioral Finance" Handbook of the Economics of Finance (edited by G. M. Constantinides, M.Harris and R. Stulz), Elsevier Science B.V., pp. 1053- 1123.
10. Barberis, N. 2017. Behavioural Finance: Asset Prices and Investor Behavior. American Economic Association. New Haven, CT: Yale University.

11. BenSaïda, A. 2017. Herding effect on idiosyncratic volatility in US industries. Finance Res. Lett., 23, pp. 121-132
12. Berelson, B.R., Lazarsfeld, P.F. and Mcphee, W.N. (1954) Voting: A Study of Opinion Formation in a Presidential Campaign. University of Chicago Press, Chicago.
13. Bhidé, A. 2010. A Call for Judgment: Sensible Finance for a Dynamic Economy. October 21. Oxford University Press, Inc
14. Bikhchandani, S., Hirshleifer, D. & Welch, I.1992. A Theory of Fads, Fashion, Custom, and Cultural Change as Informational Cascades. Journal of Political Economy, Vol. 100, No. 5, 992-1026.
15. Bikhchandani, S., & Sharma, S. (2001). Herd behaviour in financial markets: A review. IMF Staff Papers, 47(3), 279-310
16. Borensztein, R. & Gelos, G. 2003. A Panic Prone Pack? The Behavior of Emerging Market Mutual Funds, in IMF Staff Papers, Vol. 50, No. 1.
17. Bouri, E., Gupta, R., & Roubaud, D. (2019). Herding behaviour in cryptocurrencies. Finance Research Letters.
18. Cai F., Han, S., Li D. & Li Y., 2019.Institutional herding and its price impact: evidence from the corporate bond market. J. Financ. Econ., 131: 1, pp. 139-167.
19. Cakan, E., Demirer, R, Gupta, R. & Marfatia. H. 2019. Oil speculation and herding behaviour in emerging stock markets. J. Econ. Finance, 43: 1, pp. 44-56.
20. Calderón, O. P., 2019. Cryptocurrency markets meets behavioural economics: Biases and herding.
21. Chang, E. C., Cheng, J. W., & Khorana, A. 2000. An examination of herd behaviour in equity markets: An international perspective. Journal of Banking & Finance, 24:10, 1651-1679.

22. Chang, C., McAleer, M., & Wang, Y. (2020). Herding behaviour in energy stock markets during the Global Financial Crisis, SARS, and ongoing COVID-19*☆. Renewable and Sustainable Energy Reviews, 134, 110349
23. Chauhan, Y., Ahmad, N., Aggarwal, V. & Chandrad, A. 2019. Herd behaviour and asset pricing in the Indian Stock Market. IIMB Management Review, 0–25.
24. Cheah, T. & Fry, J. 2015. Speculative bubbles in Bitcoin markets? An empirical investigation into the fundamental value of Bitcoin. Economics Letters. vol. 130, C, 32-36
25. Chen, Z., Chen, W., Smiley, C., Shah, S., Borova, I., Langdon, D., Moussa, R., Beane, M., Huang, T., Routledge, B., & Wang, W. (2021). FinQA: A Dataset of Numerical Reasoning over Financial Data. , 3697-3711.
26. Chiang, C. &. Zheng, D. 2010. An empirical analysis of herding behaviour in global stock markets. Journal of Banking and Finance, 34:8, 1911–1921.
27. Christie, G. & Huang, D. 1995. Following the pied piper: do individual returns herd around the market? Financial Analysts Journal, 51, 31–37
28. Ciaian, P., Rajcaniova, M., & Kancs, d'Artis. (2016). The economics of BitCoin price formation. Applied Economics, 48(19), 1799–1815.
29. Corbet, S., Larkin, C., Lucey, B., & Yarovaya, L. (2018). Exploring the dynamic relationships between cryptocurrencies and other financial assets. *Economics Letters, 174*, 118-122
30. Costa, D. F., de Melo Carvalho, F., de Melo Moreira, B. C., & do Prado, J. W. (2017). Bibliometric analysis on the association between behavioural finance and decision making with cognitive biases such as overconfidence, anchoring effect and confirmation bias. Scientometrics, 111, 1775-1799.

31. Czerwonka, M. (2017). Anchoring and overconfidence: The influence of culture and cognitive abilities. International Journal of Management and Economics, 53(3), 48-66.
32. De Bondt, M. & Thaler, R.. 1985. "Does the Stock Market Overreact?" Journal of Finance. July, 40, pp. 793–805.
33. De Bondt, M. & Teoh, L. 1997. Herding behaviour and stock returns: an exploratory investigation. Swiss Journal of Economics and Statistics 133, 293- 324.
34. De Bondt, W. F. (1998). A portrait of the individual investor. European Economic Review, 42(3-5), 831-844
35. De Long, B., Shleifer, A., Summers, L. & Waldmann, R. 1990. Positive Feedback Investment Strategies and Destabilizing Rational Speculation. The Journal of Finance 45: 2, 379–95
36. Demirer, R., Kutan, M. & Chen, D. 2010. Do investors herd in emerging stock markets?: evidence from the Taiwanese market. J. Econ. Behav. Organ., 76: 2, pp. 283-295
37. Deng, X., Hung, S. & Qiao, Z. 2018. Mutual fund herding and stock price crashes. J. Bank. Finance, 94, pp. 166-184
38. Devenow, A. & Welch, I. 1996. Rational Herding in Financial Economics. European Economic Review, 40, 603-615
39. DiMaggio, P. (1997). Culture and cognition. Annual Review of Sociology, 23, 263–287.
40. Edwards, S. 1999 : Contagion, Paper presented at the 1999 World Economy Lecture, University of Nottingham.
41. Fama, E. F. (1965). The Behavior of Stock-Market Prices. The Journal of Business, 38(1), 34-105.
42. Fama E. 1970. Efficient Capital Markets: A Review of Theory and Empirical Work. The Journal of Finance, vol.25, no. 2

43. Friedman, M. 1984. A comment: Stock prices and social dynamics, Brookings Papers on Economic Activity 2, 504-508.
44. Godsiff, P. 2015. Bitcoin: Bubble or Blockchain? In 9th International KES Conference on Agents and Multi-Agent Systems: Technologies and Applications KES-AMSTA-15
45. Goel, P., & Dev, A. (2021). Do Blockchain Stocks Exhibit More Herding Behaviour than Traditional Stocks?. Journal of Student Research.
46. Goodell, J. W. (2020). COVID-19 and finance: Agendas for future research. Finance Research Letters, 35, 101512
47. Goodell, J. W., & Goutte, S. (2021). Co-movement of COVID-19 and Bitcoin: Evidence from wavelet coherence analysis. Finance Research Letters, 38, 101625
48. Graham, R., 1999. "Herding Among Investment Newsletters: Theory and Evidence", The Journal of Finance, Vol. LIV, No. 1, 237-268.
49. Grossman, J. & Joseph E. Stiglitz. 1980. "On the Impossibility of Informationally Efficient Markets." American Economic Review. 70:3, pp. 393–408
50. Gujarati, D. N., & Porter, D. C. (2009). Basic econometrics (5th ed.). McGraw-Hill Irwin.
51. Haugen, A. & Lakonishok, J. 1988. The Incredible January Effect. Homewood: Dow Jones-Irwin.
52. Heyink, J. W., & Tymstra, T. J. (1993). The function of qualitative research. Social Indicators Research, 29, 291-305.
53. Hirshleifer, D. 2001. Investor Psychology and Asset Pricing. Journal of Finance, Vol. LVI, No4, 1533- 1598
54. Hirshleifer, D. & Teoh, H. 2003. Herd Behaviour and Cascading in Capital Markets: A Review and Synthesis. Fisher College of Business, The Ohio State University. Eur. Financ. Manag., 9: 1, pp. 25-66

55. Hong, H., & Stein, J. (1997). A Unified Theory of Underreaction, Momentum Trading and Overreaction in Asset Markets. Capital Markets: Asset Pricing & Valuation. https://doi.org/10.1111/0022-1082.00184.
56. Hossein, A. (2020). Excel For Statistical Data Analysis
57. Hudson, R., & Gregoriou, A. (2010). Calculating and Comparing Security Returns is Harder than you Think: A Comparison between Logarithmic and Simple Returns. American Finance Association Meetings (AFA).
58. Hudson, S., & Gregoriou, A. 2015. Calculating and comparing security returns is harder than you think: A comparison between logarithmic and simple returns. International Review of Financial Analysis, 38, 151-162.
59. Hwang, S. and Salmon, M. 2004. Market Stress and Herding Journal of Empirical Finance, 11: 4, 585-616.
60. Jalal, D., Sargiacomo, M., Sahar, U. & Fayyaz, E. 2020. Herding Behavior and Cryptocurrency: Market Asymmetries, Inter-Dependency and IntraDependency. The Journal of Asian Finance, Economics, and Business, vol. 7, pp. 27–34
61. Javaira, Z., & Hassan, A. 2015. An examination of herding behaviour in Pakistani stock market. International Journal of Emerging Markets, 10:3, 474-490.
62. Jensen, M. 1978. Some Anomalous Evidence Regarding Market Efficiency. Journal of Financial Economics, Vol.6, Nos. 2/3 , 95-101.
63. Kahneman, D. & Riepe, M.1998. "Aspects of Investor Psychology." Journal of Portfolio Management. Summer, 24:4, pp. 52–65.
64. Kaiser, L., & Stöckl, S. (2020). Cryptocurrencies: Herding and the transfer currency. Finance Research Letters.
65. Kallinterakis, V. & Wang, Y. 2019. Do investors herd in cryptocurrencies– and why? Res. Int. Bus. Finance, 50, pp. 240-245

66. Kaminsky, G., Reinhart C. 2000. On Crises, Contagion and Confusion, in: Journal of International Economics, Vol. 51, No. 1, pp. 145-163.
67. Keim, D. B. 1983. Size-related anomalies and stock return seasonality: Further empirical evidence. Journal of financial economics, 12:1, 13-32.
68. Keynes, M. 1936. The general theory of employment, interest and money. New York: Harcourt, Brace
69. King, T., and Koutmos, D. (2021). Herding and feedback trading in cryptocurrency markets. Annals of Operations Research, 300, 79-96
70. Kristoufek, L. BitCoin meets Google Trends and Wikipedia: Quantifying the relationship between phenomena of the Internet era. Sci Rep 3, 3415 (2013)
71. Kristoufek, Ladislav. (2015). What Are the Main Drivers of the Bitcoin Price? Evidence from Wavelet Coherence Analysis. PLoS ONE. 10.1371/journal.pone.0123923.
72. Kumar, S., & Goyal, N. 2016. Evidence on rationality and behavioural biases in investment decision making abstract. Q. Res. Financial Mark. 8, 270–287.
73. Lakonishok, J., Shleifer, A., & Vishny, R. W. (1992). The impact of institutional trading on stock prices. Journal of Financial Economics, 32(1), 23-43.
74. Lakonishok, J., Shleifer, A. & Vishny, R. 1994. Contrarian Investment, Extrapolation, and Risk. Journal of Finance, vol. 49, no. 5 (December):1541–1578
75. Lao, P., & Singh, H. (2011). Herding Behavior in the Chinese and Indian Stock Markets. SSRN Electronic Journal.
76. Leković, M. (2020). Cognitive biases as an integral part of behavioural finance. Economic Themes, 58(1), 75-96.

77. Li, X. & Wang, A. 2017. The technology and economic determinants of cryptocurrency exchange rates: The case of Bitcoin. Decision Support Systems 95, pp. 49–60.
78. Lo, A. W. (2004). The adaptive markets hypothesis: Market efficiency from an evolutionary perspective. Journal of Portfolio Management, 30(5), 15-29
79. Loomes, G. & Robert, S. 1982. Regret Theory: An Alternative Theory of Rational Choice Under Uncertainty. The Economic Journal 92, 805-824
80. Loomes, G. 1987. Some Implications of a More General Form of Regret Theory. The Journal of Economic Theory 41, 270-287.
81. Lorenzoni, G. 2008. Inefficient credit booms. The Review of Economic Studies, 75: 3, 809-833.
82. Mandaci, P., & Cagli, E. (2021). Herding intensity and volatility in cryptocurrency markets during the COVID-19. Finance Research Letters, 46, 102382 - 102382
83. Mehra, R., & Prescott, E. 1985. “The Equity Premium: A Puzzle.” Journal of Monetary Economics, vol. 15, no. 2 (March):145–161.
84. Miller, M. 1991. Financial Innovations and Market Volatility. (pp. 1-288). Cambridge, MA: Blackwell.
85. Modigliani, F., and M.H. Miller. 1958. “The Cost of Capital, Corporate Finance and the Theory of Investment.” American Economic Review, vol. 48, no. 3 (June):261–297.
86. Moore, T., & Christin, N. (2013). Beware the middleman: Empirical analysis of Bitcoin-exchange risk. In Financial Cryptography and Data Security (pp. 25-33). Springer, Berlin, Heidelberg
87. Morgenstern, O. & Granger, C. 1970. Predictability of stock market prices. Lexington, MA: DC Heath.

88. Nadarajah, S & Chu, J. 2017. On the inefficiency of Bitcoin. Economics Letters 150, 6-9
89. Nakamoto, S. (2008). Bitcoin: A Peer-to-Peer Electronic Cash System.
90. Narayanan, A., Bonneau, J., Felten, E., Miller, A., & Goldfeder, S. (2016). Bitcoin and Cryptocurrency Technologies: A Comprehensive Introduction. Princeton University Press.
91. Neumann, J. V., & Morgenstern, O. (1944). Theory of Games and Economic Behavior. Princeton University Press.
92. Omane-Adjepong, M., Alagidede, I., Lyimo, A., and Tweneboah, G. (2021). Herding behaviour in cryptocurrency and emerging financial markets. Cogent Economics and Finance, 9(1), 1899149
93. Özen, E., & Ersoy, G. (2019). The impact of financial literacy on cognitive biases of individual investors. In Contemporary issues in behavioural finance (Vol. 101, pp. 77-95). Emerald Publishing Limited.
94. Papadamou, S., Kyriazis, N., Tzeremes, P., and Corbet, S. (2021). Herding behaviour and price convergence clubs in cryptocurrencies during bull and bear markets. Journal of Behavioral and Experimental Finance, 30
95. Patni, I., Jain, V., & Gupta, D. (2014). Testing the Existence of Herd Instinct: An Empirical Study on BSE Sectoral Indices. Capital Markets: Market Efficiency eJournal.
96. Patterson, D. M. & Sharma, V. 2005. Intraday Herding and Market Efficiency, Working Paper, University of Michigan-Dearborn.
97. Pompian, M. 2012. Behavioural Finance and Investor Types: Managing Behavior to Make Better Investment Decisions. Hoboken, NJ: John Wiley & Sons.
98. Poyser, O. (2018). Herding behaviour in cryptocurrency markets. Journal of Behavioral and Experimental Finance, 22

99. Raafat, R., Chater, N., & Frith, C. (2009). Herding in humans. Trends in Cognitive Sciences, 13, 420-428.
100. Rehan, R., & Umer, I. (2017). Behavioural biases and investor decisions. Market Forces, 12(2).
101. Ritter, J. 2003. Behavioral Finance. Pacific-Basin Finance Journal Vol. 11, No. 4, pp. 429-437
102. Rogers, E. M. (1962). Diffusion of innovations. New York, NY: Free Press.
103. Rubinstein, M. (2000). Rational markets: Yes or no? The affirmative case. Financial Analysts Journal, 57(3), 15-29.
104. Samuelson, Paul A. 1965. Proof That Properly Anticipated Prices Fluctuate Randomly. Industrial Management Review, 6:2 41-49.
105. Scharfstein, S., Stein, J.C., 1990. Herd behaviour and investment. The American Economic Review 80:3, 465-479.
106. Seers, K. (2011). Qualitative data analysis. Evidence Based Nursing, 15, 2 - 2.
107. Sharif, A., Aloui, C., & Yarovaya, L. (2020). COVID-19 pandemic, oil prices, stock market, geopolitical risk and policy uncertainty nexus in the US economy: Fresh evidence from the wavelet-based approach. International Review of Financial Analysis, 70, 101496
108. Sharma, A., & Kumar, A. 2019. A review paper on behavioural finance: study of emerging trends. Q. Res. Financial Mark. 12, 137–157.
109. Shefrin, H., & Statman, M. 2011. “Behavioural finance in the financial crisis: market efficiency, minsky, and keynes,” in Rethinking the Financial Crisis, Working Paper, Santa Clara, CA: Santa Clara University
110. Shen, F. (2022). Incorporating Sentiment and Temporal Information for Bitcoin Price Prediction. BCP Business & Management.
111. Shiller, R. 1984. Stock Prices and Social Dynamics. Brookings Papers on Economic Activity 2, 457-510

112. Shiller, R. J. (1995). Conversation, information, and herd behaviour. The American Economic Review, 85(2), 181-185.

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

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

115. Shleifer, A. 2000. Inefficient markets: An introduction to behavioural finance. New York: Oxford University Press

116. Sias, R. W. (2004). Institutional herding. The Review of Financial Studies, 17(1), 165-206

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

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

119. Sumpter, D. J. T. (2010). Collective animal behaviour. Princeton, NJ: Princeton University Press.

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

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

122. Thimmaraya, R., & Masuna, V. (2011). A novel quantitative behavioural framework for financial markets prediction. Capital Markets: Asset Pricing & Valuation, eJournal, 3(152).

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

124. Turner, R. H., & Killian, L. M. (1957). Collective behaviour (Vol. 3). Englewood Cliffs, NJ: Prentice-Hall.

125. Tversky, A. & Kahneman, D. 1979. Prospect Theory: An Analysis of decision under risk. Econometrica, Vol. 47, No2., pp. 263-292.
126. Tversky, A. & Kahneman, D., 1986. "Rational Choice and the Framing of Decisions," The Journal ofBusiness 59(4)
127. Tversky, A. & Kahneman, D. 1992. Advances in Prospect Theory: Cumulative Representation of Uncertainty. Journal of Risk and Uncertainty, 5:927-323.
128. Voronkova, S. & Bohl, M.T. 2005. Institutional traders' behaviour in an emerging stock market: empirical evidence on Polish pension fund investors. Journal of Business, Finance and Accounting 32:7&8, 1537-1560.
129. Wang, J. 1993. A model of intertemporal asset prices under asymmetric information. The Review of Economic Studies, 60:2, 249-282.
130. Welch, I. 2000. "Herding among Security Analysts." Journal of Financial Economics 58: 369–396.
131. Wooldridge, J. M. (2010). Econometric Analysis of Cross Section and Panel Data. MIT Press.
132. Wu, G., Yang, B., & Zhao, N. (2020). Herding Behavior in Chinese Stock Markets during COVID-19. Emerging Markets Finance and Trade, 56, 3578 - 3587. https://doi.org/10.1080/1540496X.2020.1855138.
133. Zhang, Dayong & Hu, Min & Ji, Qiang, 2020. "Financial markets under the global pandemic of COVID-19," Finance Research Letters, Elsevier, vol. 36(C).
134. Zhou, R., & Lai, R. (2009). Herding and Information based trading. Journal of Empirical Finance, 16(3), 388–393.