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FACULTY OF SOCIAL SCIENCES
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Analysis of herd behavior across cryptocurrencies

Bachelor's thesis

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Declaration of Authorship

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Prague, May 2, 2023

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Abstract

This thesis studies herding behavior in the cryptocurrency market between 2017 and 2022. Results from the static model reveal significant imitative behavior in the up market and during the bull year 2017. In addition, this thesis ranks among the first papers that study the effect of the early stage of the war in Ukraine on the market-wide herding behavior. Furthermore, due to Bitcoin's dominant position among other coins, closer attention is devoted to studying its influence on the herding behavior in the market. However, herding seems to be present only during extreme Bitcoin movements. In response to these results, five dominant coins (Bitcoin, Ethereum, XRP, Litecoin and Dogecoin) are excluded from the sample and their influence on the rest of the market is studied. The evidence suggests strong herding behavior of the rest of the market around these five giants. Therefore, the return of smaller coins seems to be influenced by the performance of larger coins, rather by solely that of Bitcoin.

JEL Classification G02, G15, G40, C22, C58
Keywords Cryptocurrencies, Herding behavior, Bitcoin, COVID-19

Title Analysis of herd behavior across cryptocurrencies

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Abstrakt

Tato studie se zabývá analýzou stádního chování na trhu kryptoměn mezi lety 2017 a 2022. Výsledky statického modelu naznačují existenci výrazného stádního chování ve dnech pozitivní návratnosti trhu a v období roku 2017. Tato studie je navíc jedna z prvních, která zkoumá dopad ranné fáze války na Ukrajině na stádní chování na trhu kryptoměn. Kvůli dominantní pozici Bitcoinu mezi ostatními kryptoměnami, práce dále pokračuje zkoumáním vlivu Bitcoinu na stádní chování na trhu. Nicméně, přesvědčivý důkaz takového chování okolo Bitcoinu byl nalezen pouze ve dnech extrémních hodnot návratnosti této kryptoměny. V návaznosti na toto zjištění, pět vysoce obchodovaných kryptoměn (Bitcoin, Ethereum, XRP, Litecoin and Dogecoin) je odebráno z portfolia a je studován jejich vliv na zbylý trh. Výsledky naznačují výrazné stádní chování zbytku trhu k těmto pěti gigantům. Zdá se tedy, že návratnost malých měn na trhu je přímo ovlivněna výkonností velkých měn spíše než výkonností Bitcoinu samotného.

Klasifikace JEL	G02, G15, G40, C22, C58
Klíčová slova	Kryptoměny, Stádní chování, Bitcoin, COVID-19

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Contents

List of Tables

List of Figures

Acronyms

CAPM Capital asset pricing model

COVID-19 Coronavirus disease

CSAD Cross-sectional absolute deviation

EMH Efficient-market hypothesis

Bachelor's Thesis Proposal

Author	Kateřina Krouská
Supervisor	PhDr. Jiří Kukačka, Ph.D.
Proposed topic	Analysis of herd behavior across cryptocurrencies

Research question and motivation Traditional financial theory presumes that every investor is fully rational in his decision making. He sees all alternatives and is perfectly familiar with all consequences of his actions. In reality, people act based on their judgment which can often be wrong, and they are partially influenced by their mood and feelings (Kahneman & Tversky, 1979). Behavioral economics recognizes many deviations from the rule of rationality. This thesis is dedicated to herding bias.

Herding behavior emerges when individuals behave similarly to the crowd. In periods of growth, people see the success of others and decide to join the flow, often with little or no insight. In periods when uncertainty increases, investors tend to copy each other's decisions rather than to rely on their own independent analysis (Kahneman, 2011;Bikhchandani & Sharma, 2000).

In financial markets, the herding bias has been tested several times and it is proven it plays a fundamental role in individual decision making (Park & Sabourian, 2011;Prechter Jr, 2001;Bikhchandani & Sharma, 2000). According to (Bouri, et al., 2019) the herding effect was present in the cryptocurrency market between 2013 and 2018. In 2019, the Covid-19 pandemic started, bringing a huge wave of uncertainty into the market. Consequently, (Yarovaya, et al., 2021) studied the period between 2019 and 2020 concluding that Covid-19 pandemics did not amplify the herding effect in crypto markets.

The aim of this study is to examine the herding effect on five well known cryptocurrencies, Bitcoin, Ethereum, Litecoin, XRP and Dogecoin between 2017 and 2022. This work will also examine sub-periods of the price increase in 2017 and 2021 and the recent period of the price drop in 2022. The intended outcome includes the comparison between herding in financial markets and crypto markets, expecting the herding in crypto to be more significant due to the potentially higher proportion of amateur retail investors.

Contribution The genesis of Bitcoin is connected to year 2009 and from then on thousands of other cryptocurrencies have been created. In 2017, Bitcoin's value went significantly up. This increase in price was caused by irrational traders who followed other's decisions with no reference to their own beliefs (Ballis & Drakos, 2020). Next tremendous growth in prices came in a bull year 2021 during the Covid-19 pandemics when FED announced its plan to keep rates near zero. Institutional investors like Tesla and Morgan Stanley bought billions of bitcoins and several households shifted their savings from traditional markets to more engaging financial and crypto markets. After that, a huge inflationary wave appeared resulting in increased interest rate. People feared the threat of a recession and started to save. This reversal in spring 2022 pushed prices back to their 2020 values.

The majority of studies related to this topic focus only on Bitcoin or study cryptocurrencies aggregately. This work aims to present a comparison between five familiar cryptocurrencies in connection with aforementioned events. I believe my study will bring a better understanding of the topic and can contribute to other studies in this field.

Methodology The data will be collected from https://coinmarketcap.com/a using daily prices of Bitcoin, Ethereum, Litecoin, XRP and Dogecoin between 2017 and 2022. For the detection of the herd behavior, CSAD measure will be used together for all stated currencies and then separately. CSAD measures dispersion by taking the absolute difference between individual return and average market return, thus this method is far more sensitive to outliers than the older CSSD method (Chang, et al., 2000). The average market return will be calculated as an average of top 100 cryptocurrencies. Advanced herding detection technique is a Markov switching model which works well even for nonlinear models (Hamilton, 1990).

Outline

1. Abstract
2. Introduction
   2.1 Motivation for the research
3. Literature review
   3.1 Other literature related the topic
   3.2 Stating hypothesis
4. Methodology
   4.1 CSAD/Markov model

4.2 Testing approach

4.3 Defining shorter testing periods

5. Data

5.1 Comments on data used

6. Results and discussion

6.1 Rejecting/not rejecting hypothesis

6.2 Comparison of studied currencies and periods

6.3 Comparison with herding in financial markets

7. Conclusion

7.1 Broader interpretation of results

7.2 Topics for further research

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Author Supervisor

Chapter 1

Introduction

Bitcoin, the first cryptocurrency presented to the world, was created by an anonymous developer using the pseudonym Satoshi Nakamoto. According to the initial idea, Bitcoin should serve as an alternative media of exchange which would solve the most pronounced problem of existing currencies; their centralisation which leaves all the power of currency supply in the hands of its regulators. For this reason, Bitcoin has often been hailed as the future of money (Cheung *et al.* 2015). The common use of Bitcoin, however, seems to has been deflected elsewhere. Ten years later its introduction, only a minority of users was using it for exchange purposes (Baur *et al.* 2018). The majority of Bitcoin holders do not exchange it; they rather "buy and hold" therefore making it a long-term speculative asset (Gurdgiev & Corbet 2018).

The first significant inflow of these usually non-active traders is dated back to 2013 which resulted in price increase of about 700% (CoinGecko 2023c) at that year (Cheung *et al.* 2015). This unprecedented interest in one particular asset prompted the introduction of other digital currencies such as Litecoin. Because cryptocurrencies valuations cannot be backed up by any cash flow (as opposed to bonds and equities) their return is defined by capital gains alone. This makes cryptocurrencies a highly speculative asset and complicates assessing the rationale for individual investment, especially in a case of unexperienced traders. In similar situations, the uninformed but wealth seeking individuals tend to follow decisions of others in a belief, that their behavior is based on some private knowledge or the correct information. This tendency called *herding behavior* (Banerjee 1992) can be categorized within fundamental instincts of human kind (Devenow & Welch 1996). Being worse of than others is largely undesirable and therefore, by imitating the rest of the group, at any cost avoided.

In 2017, media started to publish numerous stories of people becoming extremely rich thanks to cryptocurrency markets (Gurdiev & O'Loughlin 2020). This increased awareness and attractiveness of digital coins prompted many new traders into the market which made it extremely bullish. That led to the emergence of a price bubble which soon burst resulting in a lot of people losing a significant share of their life savings (Papadamou *et al.* 2021).

Today, the majority of cryptocurrency traders are young people (Bouri *et al.* 2019) who tend to be influenced by social media hashtags (Krištoufek 2015) and many other sources of cryptocurrency impulses. These people are often less experienced in trading and therefore less confident in their decisions. As a result, they are often subject to social pressure and thus "fashionable" investment choices (Kaiser & Stöckl 2020). This tendency is even strengthen during periods of market stress (De Souza *et al.* 2020), which are by the traditional herding literature of Christie & Huang (1995) defined as "trading intervals characterized by large swings in average prices".

The majority of studies that focus on identifying herding behavior use static model approach of Christie & Huang (1995) (CSSD model) or Chang *et al.* (2000) (CSAD model) which focus on the dispersion of individual returns. Alternative approach uses beta coefficients first presented by Sharpe (1964), developed by Hwang & Salmon (2004) and performed in cryptocurrency markets by De Souza *et al.* (2020) or da Gama Silva *et al.* (2019). In case of insufficiency of the static model methodology, other studies use Rolling Window Analysis (Stavroyiannis & Vassilios 2017) or Markov Switching Model (Hamilton 1989).

This thesis contributes to the existing herding literature in a number of ways. Firstly, it covers the period from 2017 to 2022, by which it provides a new perspective on the herding in cryptocurrencies. Secondly, it examines the impact on the cryptocurrency market of the bull year 2017 and the Covid-19 pandemics in comparison with the impact of an early stage of the war in Ukraine. Lastly, it studies the herding behavior in connection with five major currencies and Bitcoin separately. This thesis continues on Vidal-Tomás *et al.* (2019) who claim that investors make their investment decision based on observing bigger currencies. We expect many traders to use these coins as a "cryptocurrency benchmark" and thus to overreact to their extreme movements. As the various studies conclude that individual's regret aversion is stronger than loss aversion (Papadamou *et al.* 2021; Shrotryia & Kalra 2021; Ballis & Drakos 2020), we additionally expect to see stronger herding behavior in the upper tail of the Bitcoin returns distribution.

Based on mentioned observations, the CSAD approach will be used to test the following hypothesis:

> Hypothesis #1: Cryptocurrency market in the studied period is prone to herding.
>
> Hypothesis #2: In the studied period cryptocurrency investors herd around Bitcoin. This behavior is enhanced during extreme Bitcoin movements while this tendency is even more pronounced when Bitcoin return lies in the extreme upper-tail of the distribution.
>
> Hypothesis #3: Major cryptocurrencies have statistically significant association with herding behavior among the rest of the market.

The rest of the thesis is organized in a following manner: Chapter 2 summarizes the finding of existing literature on the topic. Chapter 3 details the application of statistical methods. Chapter 4 expound on the data. Chapter 5 provides results. Chapter 6 concludes the thesis.

Chapter 2

Literature Review

2.1 From Traditional to Behavioral Finance

For a long time, economists were convinced that people make money-related decisions based on comparing quantities that represent expected gains or losses i.e. expected utilities (Friedman & Savage 1952). From this idea emerged so-called Expected Utility Hypothesis (EUH) according to which expected utilities form the base for the majority of decisions made in financial markets. This hypothesis was firstly contradicted in 1713 by a St. Petersburg Paradox which demonstrated that rational investors can act in a different way than that predicted by EUH. Bernoulli (1738), a pioneer of EUH, defended this hypothesis using the diminishing marginal utility of money as a reason for such a behavior. Later, Friedman & Savage (1952) doubt its validity and question its relevancy in economics. Only in the subsequent decades, the two main pillars of the traditional finance arise. These are the Capital Asset Pricing Model (Sharpe 1964) and the Efficient Market Hypothesis (Fama 1970).

2.1.1 The Pillars of Traditional Finance

Following Sharpe (1964), in early 1970's there was no sufficient theory according to which the price of risk would be determined by investor preferences. Sharpe (1964) suggests a Capital Asset Pricing Model (CAPM) which develops the market equilibrium theory of asset prices under conditions of risk. The expected return of an asset is defined according to its beta coefficient which is a measure of volatility attributed to the return of that asset compared to the expected return of the market. Following this approach, it is believed that investors decide solely based on expected value and its standard deviation.

Subsequently, Fama (1965) divides investors into two groups; intrinsic traders and chartists, and concludes that stock returns follow a random walk and so for individual investors is highly improbable to beat the market in the long run. He also assumes that even one loud opinion can cause a bubble which will not last long. When the price goes up, the intrinsic traders will find the asset far from its true value and sell short; the chartists will recognize the overpricing and do the same. These offsetting mechanisms make any bubble burst very soon and imply that irrationality in the market is temporary and will be canceled out.

Fama (1970) defines an *efficient market* as a market where prices fully reflect all available information. The "fully reflect" term holds when subsequent price changes are independent and identically distributed. These two conditions being fulfilled, we are facing a random walk (Fama 1965). Fama (1970) presents three forms of test for the efficient market hypothesis. Weak form test assumes that only historical prices are taken into consideration. Semi-strong test additionally includes all publicly available information. Strong form test then examines markets with privately known information typical for monopolistic competition. The last example is said to be an extreme case and is used merely as a benchmark against market deviations. The author concludes in favor of the efficient market hypothesis arguing that evidence benefiting this hypothesis is abundant and the one undermining it is scarce.

2.1.2 Related Criticism

Critics of EMH point out the inability to explain high volatile periods when noise in the market is present. So-called *noise traders*, investors who do not see the intrinsic value of an asset and rely on the noise, present possibly the largest threat for EMH. As mentioned earlier, Fama (1965) and Friedman & Savage (1952) claim that noise traders do not possess a significant importance and their influence will be cancelled out by arbitrageurs very soon. Bradford De Long *et al.* (1990) calls this argument into question by stating that arbitrageurs are risk averse and have short horizons. Due to the fact called a "noise-traders risk" many arbitrageurs will not enter the market. This *noise-traders risk* suggests that there is a persistence in the opinion of noise traders and therefore an arbitrageur needs to expect the price movement to continue even after he takes/losses the position, e.g., when he sells the asset, the price will probably continue to rise before it drops; when he buys the asset, he must be prepared to watch it plummet before the expected growth takes place. Contrary to Fama

(1965), Bradford De Long *et al.* (1990) show that beating a noise trader takes time and not every arbitrageur thinks in such a long run. Because profitability is a function of risk, noise traders can earn above average profits just because they can bear more of a risk they themselves create.

Criticism raised against EUH is abundant. Allais (1953) shows that people usually prefer certainty when assessing a positive outcome and risky choices when the possible outcome is negative. This contradicts any basic mathematical formula and suggests that people may not be rational in their financial decisions. His findings were then forgotten and re-appeared in people's awareness only with famous Prospect Theory. This seminal article of the Nobel price laureate Daniel Kahneman and his colleague Amos Tversky laid the foundation of a domain called Behavioral economics. Kahneman & Tversky (1979) criticize the expected utility theory by developing the ideas presented by Allais (1953).

2.1.3 The Perspective of Behavioral Finance

According to Kahneman & Tversky (1979) people are risk seeking when a potential financial loss is involved in their decision making contrary to the situation when a potential financial gain is presented. In the latter scenario, agents tend to prefer certainty and choose the less risky option. Additionally, investors often neglect events with small probabilities treating them as if they were impossible and overestimate events with high probabilities as if they were certain. Nevertheless, even initially rational traders can in the long run lose this attribute (Hirshleifer 2001). People tend to credit themselves for success but subsequently, fail to blame themselves for a failure (Kent *et al.* 1998). Barberis *et al.* (1998) develop this idea by implementing a model where actual earnings follow a random walk. Individuals in this study believe that their returns either grow or are mean-reverting (Barberis *et al.* 1998). As suggested by Fama (1965) and EMH, individual investors are not capable of intentionally beating the market. On contrary, Coval *et al.* (2021) show that there are individual investors who are able to constantly beat the market while there are individuals who constantly underperform it.

EMH and EUT are not able to align with the majority of these findings and thus Behavioral economics is understood as a better description of reality (Hirshleifer 2001; Kahneman & Tversky 1979). Hirshleifer (2001) states many other biases causing a lack of rational thinking however this thesis will focus only on investors' tendency to follow the decisions of others.

2.2 Herding

"The reaction of one man can be forecast by no known mathematics; the reaction of a billion is something else again."

- Isaac Asimov

People are said to herd anytime they take actions that do not align with their private information (Hwang & Salmon 2004; Banerjee 1992). Instead, they blindly mimic what other market participants do, hoping that the others understand the situation better or their private information are more accurate (Christie & Huang 1995). Devenow & Welch (1996) reason this tendency as individual's preference for a conformity with market consensus. Prechter (2001) attributes this behavior to a primitive instinct for survival whose impulses generate a quicker response than the ones tied to rational thoughts do. In scientific terms, the term herding is used when talking about the correlations between individual returns; in situations when the individual opinion is absent and people follow the market consensus, the dispersion of individual returns diminishes while market return increases (Chiang & Zheng 2010; Chang *et al.* 2000; Christie & Huang 1995). This results in a group of investors who "trade in the same direction over a period of time" (Nofsinger 1999). Tan *et al.* (2008) argue that such a behavior contributes to a price deviation from its fundamental value which can create many opportunities for non-participating traders, however according to Park & Sabourian (2011) herding also generate more volatile prices which by itself generate more uncertainty in the market. Herding is also partially responsible for the formation of bear and bull markets (Fama 1998). Bull markets can lead to overoptimism and subsequently to several bubbles (Shiller 2016; Lakonishok *et al.* 1992).

2.2.1 Herding Behavior Classification

Bikhchandani & Sharma (2000) distinguish between spurious and intentional herding behavior. Spurious herding is a foreseeable process of, e.g., buying more stocks when interest rates go down. It is not an act of a change in behavior after observing others but rather a reaction to a commonly known fact. This type of herding is however, beyond the score of this thesis. Intentional herding arises when an individual imitates other's actions, both consciously and subconsciously (Bikhchandani & Sharma 2000). The conscious herding will be addressed as *rational*; the latter one as *irrational*.

Bikhchandani & Sharma (2000) define three types of rational herding behavior: Reputation-based, Compensation-based, and Information-based. The first two are common among portfolio managers who are evaluated based on how their portfolio performs compared to the market (Scharfstein & Stein 1990). In a case that one's reputation or compensation is dependent on competing against a market benchmark, an informational cascade, i.e., discarding own beliefs and acting according to group sentiment is a rational strategy (Bikhchandani *et al.* 1992; Scharfstein & Stein 1990). The Information-based herding occurs in case that an investor has information which he does not know how to assess and thus waits and observes market until it gives him a hint revealing the opinion of others. This process of learning in times of uncertainty can be attributed to a rational behavior, however every subsequent agent would need to use the information of the other agent's behavior only as a tool to set his own decision (Bikhchandani & Sharma 2000). In a real world, this usually is not the case and agents soon start to disregard their own beliefs by which the "cumulative knowledge" of the group is lost.

The irrational herding behavior described at the beginning of this section has roots in psychology. Following Chang *et al.* (2000), herding is pronounced under stressful situations such as periods of extreme volatility. Prechter (2001) states that remain acting as an uninfluenced individual is in these times extremely difficult because "emotional impulses from limbic system make a desire to seek the approval and signals of others from the group". People act as a crowd to avoid negative outcomes, most often when lack of knowledge or general logic is present (Prechter 2001). This is pronounced in emerging stock markets, where the evidence of herding is still prevalent compared to developed markets where such a behavior is on decline (Chang *et al.* 2000; Bikhchandani & Sharma 2000).

2.2.2 Empirical Examples of Herding Behavior

One of the former cases in which market return significantly deviated from its expected course was the Tulip mania in 1630s. At that time, prices of tulips escalated to a point where there was no rational concordance with the prices of other goods and people were selling their houses just to participate on this business (Calderón 2018). Subsequent financial crashes were even more extended. *Great Crash* (1929) was the result of a long speculative period when millions of people were selling all their possessions just to invest in stocks. This behavior pushed prices to unsustainable levels and the bubble burst was inevitable. More recent examples are *Black Monday* (1987) or the *Dot-com* bubble (2000) when investors pumped large amount of money into internet-based start-ups. All these mispricings followed by colossal crashes were caused by general public's fascination which was backed up by nothing more than market bullish sentiment. Since then, herding behavior had been studied for US and South Korean market (Hwang & Salmon 2004), Portuguese, Italian, Spanish and Greek market (Economou *et al.* 2011), Chinese markets (Yao *et al.* 2014) and many more.

2.3 Herding in the Cryptocurrency Market

Cryptocurrency trading became widely popular during 2017 thanks to the astonishingly rapid growth in crypto returns. The subsequent media supply of successful Bitcoin traders' stories at the beginning of 2018 attracted many new investors into the market. This high public engagement together with the lack of fundamentals, insufficient technical knowledge of participants, and weak legal framework laid the perfect ground for a market dependent on socially constructed opinions (Bouri *et al.* 2019; Corbet *et al.* 2018).

Park & Sabourian (2011) pronounce that "individuals herd when information is dispersed so considering extreme outcomes more likely than moderate ones". The lack of fundamentals in crypto allows larger dispersion of information which contributes to the speculative nature of trading (Baur *et al.* 2018). Additionally Barber *et al.* (2008) examine herding in US equity market and find that individual investors display stronger herding behavior than fund managers do. Because cryptocurrency market has only a limited number of institutional investors, it is much more susceptible to similar mispricings.

According to Menkhoff *et al.* (2006), herding decreases with experience. Following Bouri *et al.* (2019), many cryptocurrency market participants are young and easily persuaded by socials. As a result, they are prone to assess the investment based on its attractiveness more than on its related financial variables (studied for Bitcoin by Krištoufek (2015). Philippas *et al.* (2020) examine exogenous factors causing a herd and show that such sources as Twitter hashtags are able to deepen herding behavior in crypto markets. Similar behavior leads to speculative bubbles (Cheah & Fry 2015). That further benefit market participants with short horizons (Corbet *et al.* 2018; Froot *et al.* 1992) and bullish-sentiment driven investors that often dominate the rational driven ones thanks to their willingness to trade (Aloosh & Ouzan 2020; Gurdiev & O'Loughlin 2020). Moreover, Bouri *et al.* (2019) find that contrarian investing, i.e. anti-herding, cannot be profitable as long as herding prevails.

2.3.1 Inconsistencies in Ongoing Debate

According to O'Dwyer & Malone (2014), average monthly volatility of Bitcoin is higher than that of gold or foreign currencies. Following Youssef (2020), who attributes herding to the high volatility, Bitcoin is more prone to herding than the other above-mentioned assets are. However, there is a discrepancy on whether investors herd more on the down-market or the up-market. Baur *et al.* (2018) state that positive shocks increase volatility more than the adverse ones which results in a stronger herding in the up-market. This stance is in agreement with Papadamou *et al.* (2021), Shrotryia & Kalra (2021), Ballis & Drakos (2020) or Kalinterakis & Wang (2019) but in contradiction with Vidal-Tomás *et al.* (2019) and da Gama Silva *et al.* (2019). De Souza *et al.* (2020) link herding behavior with stress but Gurdgiev & Corbet (2018) emphasize the regret aversion to be a more precise reason for this phenomenon. The fear that investor will miss investment gains would correspond to stronger herding in the up-market. Additionally, Papadamou *et al.* (2021) argue that fear during bear markets sharpens people consciousness and thus prevents the uniform irrationality. Bouri *et al.* (2019) perceive investors' lower susceptibility to negative shocks as a response to not being able to sell short.

The inconsistencies in the researchers' opinions are tied also to other matters. Bouri *et al.* (2019) argue that herding increases with economic policy uncertainty while Youssef (2020) claims otherwise. Youssef (2020) also mentions the rise in trading volume and gold price as factors reducing herding as opposed to Haryanto *et al.* (2020) who study herding between 2011 and 2013 and find evidence that an increase in the trading volume works as a herding trigger.

2.3.2 Overview of Existing Research

To summarize existing findings, we further present messages from various influential studies within field. Haryanto *et al.* (2020) examines the period from 2011 to 2013 and find herding in the emerging cryptocurrency market. In the period from 2013 to 2018, Bouri *et al.* (2019) and Youssef (2020) find no herding in the static model. Youssef (2020) subsequently applies time-varying model and identifies long-lasting herding that persists throughout the whole period. Coskun *et al.* (2020) observe antiherding in 14 leading crypto-currencies. Shrotryia & Kalra (2021) and Kumar (2021) discover herding only in the situations of market stress and high volatility. Stavros & Vassilios (2019) find the absence of herding in the period from 2015 to 2018, contrary to Ballis & Drakos (2020) who study the six major cryptocurrencies and conclude that investors act irrationaly with "no reference to their own belief".

In spring 2020, COVID-19 pandemics contributed to a significant inflow of uncertainty into the market. Some studies focused on behavioral responses induced by COVID-19 pandemics found evidence of herding behavior (Susana *et al.* 2020) while others (Yarovaya *et al.* 2021) suggest no presence of amplified herding during this pandemy. In summary, information derived from studying cryptocurrency market remain inconclusive and thus open to further analysis (Kumar 2021).

Chapter 3

Methodology

The methodology of this thesis builds on Christie & Huang (1995) who propose to use cross-sectional deviations of returns (CSSD) to test herd behavior. This method is nowadays found to be too stringent, therefore this thesis builds on an alternative approach which uses the cross-sectional absolute deviation of returns (CSAD).

3.1 CSAD Measure

CSAD measure was first proposed by Chang *et al.* (2000) who reworked the CSSD model proposed by Christie & Huang (1995). CSAD model measures the dispersion of individual returns and the market return. In presence of herding behavior (i.e., in situation when individual investors suppress their own intuition and follow the market consensus), security returns will not deviate much from the market return. As a consequence, the dispersion will be increasing at a decreasing rate or (in a case of strong herding) it can potentially reverse entirely and start to decrease (Chang *et al.* 2000). Contrary to rational asset pricing models, CSAD is able to capture these non-linearities. CSAD measure is given by:

$$CSAD_t = \frac{\sum_{i=1}^{N} |R_{i,t} - R_{m,t}|}{N} \tag{3.1}$$

where $R_{i,t}$ is the observed stock return of firm i at time t, N represents the number of stocks observed and $R_{m,t}$ is the market return at time t.

We follow on from Bouri *et al.* (2019); Philippas *et al.* (2020); Ballis & Drakos (2020); Kumar (2021) who examined herding in the cryptocurrency

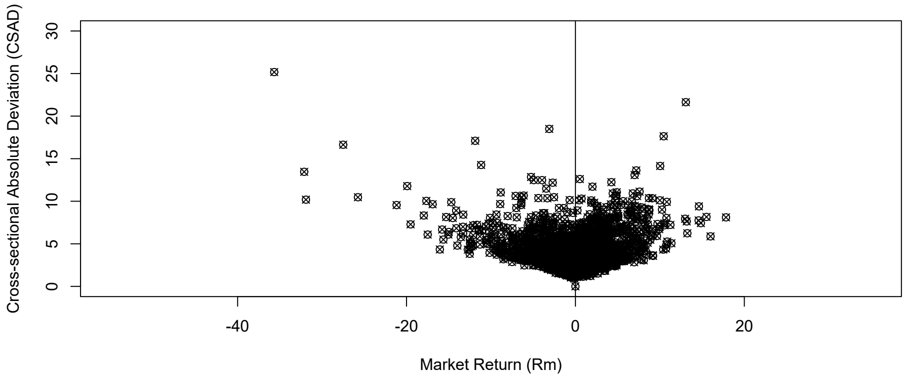

Figure 3.1: The relationship between the market return ($R_{m,t}$) and the cross-sectional standard deviation (CSAD) of 100 most capitalised cryptocurrencies (1/1/2017 - 31/12/2022)

market by applying the CSAD model. For the purpose of this work, $R_{i,t}$ is an observed return of a cryptocurrency unit at time t, N represents the number of these units and $R_{m,t}$ is an average return of the market portfolio at time t.

To illustrate the relation between market return and CSAD, we plot the CSAD for each day alongside the corresponding market average return for 100 most capitalised cryptocurrencies throughout the period from the beggining of January 2017 to the end of December 2022. Observing the Figure 3.1, we can see that a particular change in the market return does not cause a similar change in the CSAD. This observation directly confirms the unsuitability of the linearly positive relationship between these two variables.

According to Capital Asset Pricing Model (CAPM) (Sharpe 1964), the dispersion will increase relatively to the market return and the relation of these two variables is linear. We will use CAPM to illustrate the link between CSAD and the market return. Let $E_t(.)$ be the expectation in period t and let assume all other variables to hold as already defined. Then according to Black (1972), CAPM can be expressed as follows:

$$E_t(R_i) = \gamma_0 + \beta_i E_t(R_m - \gamma_0), \tag{3.2}$$

where γ_0 is the return on the zero-beta portfolio, β_i is the time-invariant systematic risk measure of the cryptoasset i at a given time t and let β_m be the risk of an equally-weighted portfolio. Hence,

$$\beta_m = \frac{1}{N}\sum_{i=1}^{N}\beta_i \tag{3.3}$$

The absolute value of the deviation (AVD) of cryptoasset i's expected return can then be expressed as:

$$AVD_{i,t} = |\beta_i - \beta_m| E_t(R_m - \gamma_0) \tag{3.4}$$

Thus, we can define the asset returns' expected cross-sectional absolute deviation (ECSAD) in period t:

$$ECSAD_t = \frac{1}{N}\sum_{i=1}^{N} AVD_{i,t} = \frac{1}{N}\sum_{i=1}^{N} |\beta_i - \beta_m| E_t(R_m - \gamma_0) \tag{3.5}$$

The linearly increasing relation between market expected returns and dispersion can be subsequently derived as follows:

$$\frac{\partial ECSAD_t}{E_t(R_m)} = \frac{1}{N}\sum_{i=1}^{N} |\beta_i - \beta_m| > 0 \tag{3.6}$$

$$\frac{\partial^2 CSAD_t}{\partial E_t(R_m)^2} = 0 \tag{3.7}$$

Because this often does not hold in reality, Chang *et al.* (2000) add squared market return to capture the non-linearities in the model. The resulting equation stands as follows:

$$CSAD_t = \alpha + \beta_1 |R_{m,t}| + \beta_2 R_{m,t}^2 + \epsilon_t, \tag{3.8}$$

where $CSAD_t$ is the cross-sectional standard deviation at time t and $R_{m,t}$ is the market average at time t. Finally, the negative coefficient β_2 indicates a herding behavior in the studied market.

Asymmetric Herding

To account for the possibility that herding may be asymmetric on the up and down market we further incorporate equation proposed by Chang *et al.* (2000) to test for this issue. The equation stands as follows:

$$CSAD_t^{UP} = \alpha + \beta_1^{UP} |R_{m,t}^{UP}| + \beta_2^{UP} (R_{m,t}^{UP})^2 + \epsilon_t \tag{3.9}$$

$$CSAD_t^{DOWN} = \alpha + \beta_1^{DOWN}|R_{m,t}^{DOWN}| + \beta_2^{DOWN}(R_{m,t}^{DOWN})^2 + \epsilon_t, \qquad (3.10)$$

where $|R_{m,t}^{UP}|$ ($|R_{m,t}^{DOWN}|$) is the absolute value of an equally weighted realized return of all available coins on day t when the market is up (down). Therefore, if during the periods of relatively large price swings investors do herd, it will be captured by the significant negative β_2.

3.2 CSAD Measure for an External Factor

Previously studied versions of the CSAD model lie on the assumption that there are no other significant external factors influencing agents' decision making in the particular market. This seems to be too strong assumption to be realistic. Observing the situation in the stock market, Chang *et al.* (2020) show that oil price movements influence herding in the energy sector. In cryptocurrency trading, Philippas *et al.* (2020) found amplified herding due to crypto-related twitter hashtags. We aim to use the approach from Chang *et al.* (2020) and apply it in a slightly modified way.

The Figure 3.2 depicts major crypto assets by a percentage of total market capitalization covering the whole studied period. It is observable that Bitcoin, the oldest and the most discussed cryptocurrency, steadily represents roughly around 50% of total market capitalization. The large proportion of investors in the cryptocurrency market do not shift between alternative coins; they rather move in or out from the market. This is closely connected with little or no experience of many investors in cryptocurrencies. Because Bitcoin acts as a gateway to the crypto market (Kaiser & Stöckl 2020) we expect many uninformed traders to rely on changes in Bitcoin price to be a relevant source of information and thus Bitcoin to have insignificant influencing power on the other coins.

For its demonstrated dominance and wide awareness among general public, we incorporate the return of Bitcoin to the original CSAD model as an exogenous factor influencing herding. Following Chang *et al.* (2020) the regression model is estimated as follows:

$$CSAD_{X,t} = \alpha + \gamma_1|R_{X,t}| + \gamma_2 R_{X,t}^2 + \gamma_3 R_{B,t}^2 + \epsilon_t, \qquad (3.11)$$

where $CSAD_{X,t}$, $|R_{X,t}|$ and $R_{X,t}^2$ refer to the original portfolio at time t excluding Bitcoin and $R_{B,t}^2$ refers to the squared return at time t of Bitcoin separately.

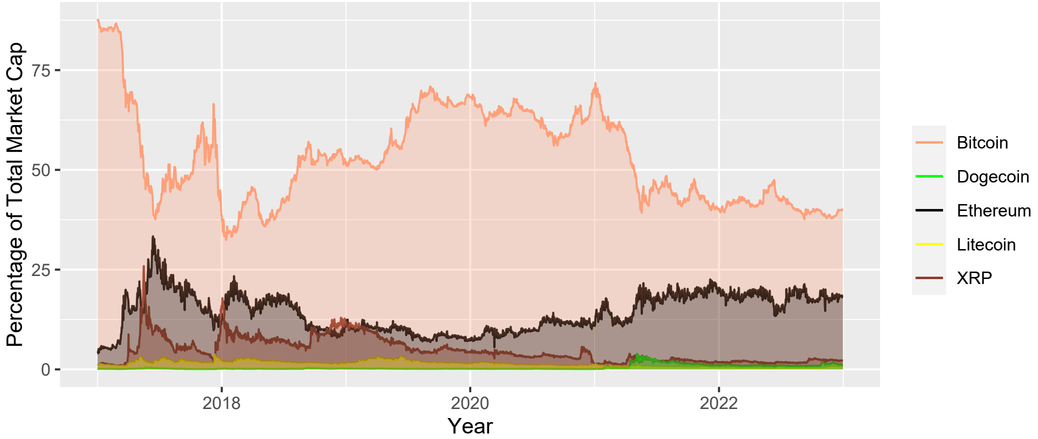

Figure 3.2: The dominance of five major coins

Therefore $X = exclBtc$, $X = 1, ..., 99$. The negative value of γ_2 indicates local herding behavior while the negative value of γ_3 implies herding around Bitcoin.

CSAD Measure During Extreme External Factor Movements

Herding appears to be pronounced during extreme market movements. Following Christie & Huang (1995) we further observe 1% and 5% of sample observations appearing in the extremities of the distribution aiming to detect extreme movements. This idea is incorporated in the following equation:

$$CSAD_{X,t} = \alpha + \gamma_1|R_{X,t}| + \gamma_2 R^2_{X,t} + \gamma_3 R^2_{B,t} + \gamma_4 D_t^{B,up} R^2_{X,t} + \gamma_5 D_t^{B,down} R^2_{X,t} + \epsilon_t, \tag{3.12}$$

where $D_t^{B,up} = 1$ when the appropriate return of Bitcoin lies in the upper extreme tail of the returns distributions and $D_t^{B,down} = 1$ when the return lies in the lower extreme tail. In case of enhanced herding during extreme Bitcoin movements, the coefficients γ_4 and γ_5 should be negative.

3.3 CSAD Measure with External Influence of Five Dominant Cryptocurrencies

After studying herding for Bitcoin being the only external factor we want to develop the idea of an augmented influence of large coins on their smaller counterparts. Observing once again the situation in the stock market, Chang *et al.* (2020) found evidence that Europe market herd around the US market.

Looking again at the Figure 3.2, we can see that Bitcoin, Ethereum and XRP are the most marketed currencies throughout the studied period. Together with widely discussed coins Litecoin and Dogecoin, their cummulative market capitalisation exceeds 90% in January 2017 and 55% in December 2022. A number of existing studies analyze herding behavior in the aggregate market by studying only the most pronounced coins (Ballis & Drakos 2020; Susana *et al.* 2020; Coskun *et al.* 2020). The reasoning behind these analyses lies in findings similar to Vidal-Tomás *et al.* (2019) who study the relation between large and small coins and conclude that the smallest cryptocurrencies follow the mean return of the largest cryptocurrencies.

On basis of this assumption, we aim to study the five mentioned cryptocurrencies (Bitcoin, Ethereum, XRP, Litecoin and Dogecoin) as a stand-alone market and analyze its influence on the rest of the cryptocurrency market. Therefore we divide our portfolio into two subsets: first group consist of the five mentioned currencies, the second group represents the rest of our portfolio. For simplicity, let us label the subset of large currencies as *BEXLD*, while $BEXLD = 1, ..., 5$, and the rest 95 currencies as Y, when $Y = 1, ..., 95$. Then we follow Chang *et al.* (2020) and estimate the equation as follows:

$$CSAD_{Y,t} = \alpha + \gamma_1 |R_{Y,t}| + \gamma_2 R^2_{Y,t} + \gamma_3 CSAD_{BEXLD,t} + \gamma_4 R^2_{BEXLD,t} + \epsilon_t, \quad (3.13)$$

where $CSAD_{Y,t}$, $|R_{Y,t}|$ and $R^2_{Y,t}$ refer to the original set without the five top currencies and $CSAD_{BEXLD,t}$ and $R^2_{BEXLD,t}$ refer to these five top currencies. To explain the possible implications, negative and significant γ_2 would imply market-wide herding. Moreover, negative and significant coefficient γ_4 would indicate the herding behavior of sector Y around the sector BEXLD. Lastly, a positive and significant γ_3 would suggest that market sector BEXLD has a dominant influence on the market sector Y.

Chapter 4

Data

4.1 Dataset

We focus on daily closing prices of 100 most capitalized cryptocurrencies over the period from the beginning of January 2017 to the end of December 2022. This sample period covers the boom in 2017, which prompted increased attention from policymakers and business owners (Papadamou *et al.* 2021), the subsequent 2021 rise in prices during Covid-19 pandemics and the 2022 drop in prices caused by the war in Ukraine. This makes our sample one of the more extensive ones within existing studies concerning cryptocurrencies.

To avoid survivorship bias, the sample is adjusted in terms of volume every 180 days. Consequently, the final dataset is a result of 12 adjustments and 381 coins in total are taken into consideration. Finally, we justify the usage of daily dataset by the fact that cryptocurrency market is very fast-paced and volatile. Eventhough this approach brings some noise into our observations, studying cryptocurrency market on a longer horizonts would not add value, given its nature of a highly variable asset. Moreover, exogenous signals are said to be short-lived, therefore it makes sense to study their influence using high-frequency data.

We download daily cryptocurrency data from CoinGecko (2023b) [accessed: 2023-01-12]. When a "dead coin" (i.e., coin that has been abandoned) is present in the listing, it is downloaded from CoinMarketCap (2023) [accessed: 2023-02-13]. In total, 2191 observations are collected.

4.2 Data Processing

Moving on to data processing part, the individual return of an asset i is calculated as follows:

$$R_{i,t} = [log(P_{i,t}) - log(P_{i,t-1})] \times 100, \tag{4.1}$$

where $R_{i,t}$ is the return at time t displayed in percentages, $P_{i,t}$ is the price of the cryptocurrency i at time t and $P_{i,t-1}$ is its lagged variable. For the calculation of CSAD, market return is obtained as an average of all returns across equally-weighted market portfolio at time t.

When examining herding in the up market, $R_{m,t}^{UP}$ is calculated as average market return at every time t in the observed period when the market is up ($R_m > 0$). The same applies for the down market ($R_m < 0$).

Next, we proceed by studying three periods of augmented importance separately. By *Year 2017* is meant the period from the 1st of January 2017 to the 31th of December 2017, the *Covid-19 pandemics* is defined as period from the 5th of February 2020 to the 18th of March 2021 and the *Ukrainian war* refers to the period from the 24th of February 2022, when Russia launched a military invasion of Ukraine, to the end of our dataset. For this estimation, data are similarly chosen on daily basis and the return is calculated the same way as already established.

For the sake of hypothesis #2, Bitcoin is removed from the portfolio and a new market average $R_{X,t}$ and its deviation $CSAD_{X,t}$ is calculated while X represents the portfolio without Bitcoin, factually $X = 1, ..., 99$. The Bitcoin return $R_{B,t}$ is added to the regression as a separate exogenous variable.

Lastly, to evaluate the hypothesis #3, five chosen major currencies (Bitcoin, Ethereum, XRP, Litecoin and Dogecoin) are extracted from the portfolio and their returns are grouped into one unit termed *BEXLD*. Consequently, the mean return $R_{BEXLD,t}$ and the cross-sectional absolute deviation $CSAD_{BEXLD,t}$ of these currencies are calculated. The 95 remaining currencies are grouped in a similar manner and called Y so that $R_{Y,t}$ is the mean return of these currencies and $CSAD_{Y,t}$ is their cross-sectional absolute deviation.

Next, we present the summary of descriptive statistics in the Table 4.1. It is worth noticing the negative average market return on the whole sample which persists even after Bitcoin and five major currencies are removed. Additionally, the market return of the five major coins presents the highest volatility in our data. The average return of these five coins is even more chaotic than that

Table 4.1: Descriptive statistics A

Hyp.	Variable	Mean	Med.	Min.	Max.	Std. d.	Skew.	Kurt.	ADF test
#1	$R_{m,t}$	-0.058	0.288	-35.667	17.829	4.435	-1.215	6.946	-11.789***
	$CSAD_t$	4.168	3.588	0	25.175	2.198	2.056	8.851	-6.769***
#2	$R_{X,t}$	-0.059	0.287	-35.589	17.908	4.449	-1.213	6.933	-11.782***
	$CSAD_{X,t}$	4.192	0.361	0	25.375	2.212	2.062	8.916	-6.768***
	$R_{B,t}$	0.128	0.205	-43.371	28.710	4.096	-0.619	9.319	-12.259***
#3	$R_{Y,t}$	-0.068	0.274	-34.936	17.703	4.447	-1.199	6.807	-11.810***
	$CSAD_{Y,t}$	4.269	3.659	0	25.984	2.256	2.092	9.331	-6.874***
	$CSAD_{BEXLD,t}$	1.996	1.395	0	51.876	2.244	7.637	126.253	-7.311***
	$R_{BEXLD,t}$	0.137	0.292	-49.540	33.056	4.864	-0.827	9.997	-11.893***

Note: *p < 0.1; **p < 0.05; ***p < 0.01. X represents the portfolio without Bitcoin (B). Y represents the portfolio without five major coins (BEXLD)

of Bitcoin itself. This observation validates the idea to study this market separately. The summary statistics for the variables describing specific periods and the asymmetric herding can be found in Appendix A.

To avoid spurious relationship and thus meaningless regression, we build on Dickey & Fuller (1979) and test for stationarity of our variables using the Augmented Dickey & Fuller test (ADF). Results in Table 4.1 suggest stationarity of the variables used and thus it is safe to proceed with the regression. Derived results should not be fabricated. Table A.1 contains single variable $CSAD^{2017}$ with ADF test-related p-value of 0.1247 which implies that non-stationarity cannot be rejected even at 10% significance level. Because the other variable of this regression is observed to be stationary even at 1% significance level, we continue to estimate the related regression. However, the accuracy of our model results could be impacted and thus it is important to interpret them with caution.

Chapter 5

Results and Discussion

5.1 The Era of Fame and Volatility

In this section, we present results of testing hypothesis #1 which studies herding on the whole examined period. Therefore, we study 100 top-capitalized cryptocurrencies for 2191 days.

We follow Chang *et al.* (2000) and apply the CSAD model to run the Equation 3.8. Commenting first on the constant, it represents a theoretical dispersion for the zero-return market. Particularly, the estimate of the intercept of 3.115 in the Table 5.1 indicates the usual distance of return dispersion to market average. This suggests that the individual returns in our portfolio are largely dispersed which is probably the consequence of the heterogeneity of the portfolio used in addition to the volatile nature of cryptocurrencies.

The coefficient β_1 attributed to $|R_m|$ represents the slope of the function which displays the level to which separate coins' returns depart from the market average. Significantly positive β_1 indicates that $CSAD_t$ moves in the same direction as $|R_m|$, therefore that cross-sectional standard deviation increases when the absolute value of market return increases. Finally, the most important coefficient β_2 attributed to R_m^2 reveals potential non-linearity. There are three possible interpretations arising from observing this coefficient: β_2 being significant and positive, significant and negative or insignificant (sign not being important). In a case of insignificant β_2, EMH is verified, i.e., there is an exact linear relationship between $CSAD_t$ and market return. When the coefficient is observed to be significant and negative, participants imitate each other in their investments decisions and therefore participate in herd behavior. On contrary, the positive and significant coefficient reveals anti-herding, meaning

Table 5.1: Estimates of herd behavior 2017 - 2022

	Dependent variable
	CSAD_t
Constant	3.115***
	(0.065)
$\lvert \text{R}_{m,t} \rvert$	0.340***
	(0.023)
$\text{R}^2_{m,t}$	0.001
	(0.001)
Observations	2191
R^2	0.268
Adjusted R^2	0.268
Residual Std. Error	1.881 (df = 2188)
F Statistic	400.8*** (df = 2;2188)

Note: *p < 0.1; **p < 0.05; ***p < 0.01

that investors' opinions are individualized and dispersed. Indeed, the higher the market return, the more pronounced the individual return dispersion.

Turning to our results in the Table 5.1, the insignificant β_2 reveals no deviation from the exact linear relationship. As a result, we find no evidence against EMH in this case.

Asymmetric Herding

Furthermore, to analyze for potential asymmetries we observe the behavior in the up (down) market (Chang *et al.* 2000). Equation 3.9 and Equation 3.10 work on testing this matter. The results indicate the presence of positive and significant linear term in both markets. Moreover, since the non-linear term in the up market is significantly negative, $CSAD_t$ has increased in a decreasing rate which points out to the existence of herding in the up market. By contrast, in the down market the non-linear coefficient β_2 is statistically significant and positive. This suggests an increasing rate of dispersion in the down market which would imply independent decision making of the market participants.

Summarising the Table 5.2, we observe cryptocurrency returns to be characterized by herding in the up market, despite that we do not find any herding in

Table 5.2: Estimates of herd behavior during up and down market

	Dependent variable CSAD_t	
	UP	DOWN
Constant	0.735***	3.635***
	(0.046)	(0.065)
$\lvert \text{R}_{m,t} \rvert$	1.405***	0.120***
	(0.034)	(0.032)
$\text{R}^2_{m,t}$	-0.071***	0.030***
	(0.003)	(0.001)
Observations	2191	2191
R^2	0.582	0.376
Adjusted R^2	0.582	0.376
Residual Std. Error	1.712	2.616
	(df=2188)	(df=2188)
F Statistic	1525.0***	660.9***
	(df=2;2188)	(df=2;2188)

Note: *p < 0.1; **p < 0.05; ***p < 0.01

the static model. This is supported by Bouri *et al.* (2019) who find no herding in the static approach and subsequently point out the importance of studying asymmetric herding behavior. Our results collide with Kalinterakis & Wang (2019), who found herding tendency in the up market in the period from 2013 to 2018. Because we identified the similar behavior in the period from 2017 to 2022, this tendency seems to be persistent in the current cryptocurrency market. The results presented are additionally in conformity with Ballis & Drakos (2020) who use GARCH model to conclude that herding is more pronounced during up movements, and Papadamou *et al.* (2021), who argue that flourishing periods imply stronger convergence. On contrary, da Gama Silva *et al.* (2019) and Vidal-Tomás *et al.* (2019) relate negative news with herding behavior, and therefore arrive to contrarian result that herding is stronger in the down market. Lastly, Gurdgiev & Corbet (2018) emphasize the importance of investors' regret aversion but does not take neither stand in this debate.

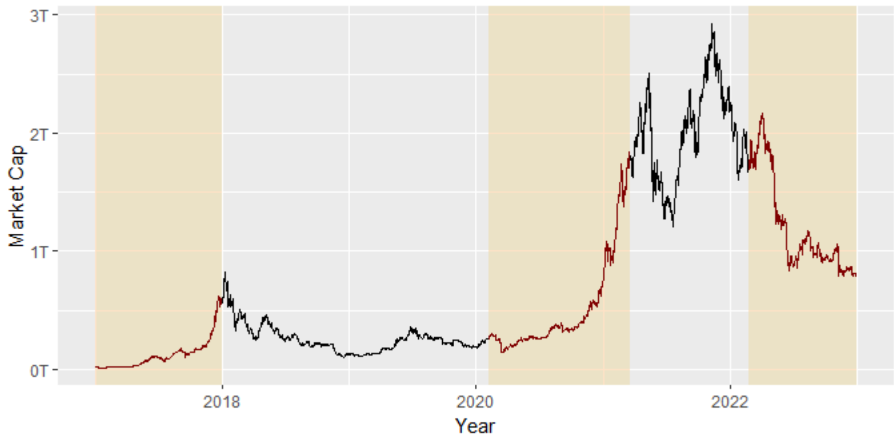

Figure 5.1: Periods of augmented attention (1/1/2017 - 31/1/2022, 5/2/2020 - 18/3/2021, 24/2/2022 - 31/12/2022)

Summary of Hypothesis #1

Based on our observed sample, we find no significant herding in the studied period from 2017 to 2022. Further examination of up and down market reveals stronger herding tendency in the up-market. This finding is in agreement with many other studies examining herding.

Herding Behavior during Specific Periods

Due to the fact that our sample covers period of significant changes in cryptocurrency value (year 2017) or periods of great general importance (Covid-19 pandemics, Ukrainian war) we doubt the total lack of herding in the whole period. Therefore, we subtract these three periods from our sample and study them separately. These are well depicted in the Figure 5.1.

Firstly, augmented attention is devoted to the whole year 2017. That year cryptocurrency market rocketed, benefiting from increased awareness among general public. First column in the Table 5.3 summarizes derived estimation results. In contrast to the intercept attributed to the modification concerning the whole period, the intercept of 5.283 is significantly higher. This signifies that the *bull year* average is more turbulent than the period average. Additionally, the significant and negative coefficient attributed to $R^2_{m,t}$ denote herding in the studied market period. This finding is in conformity with Bouri *et al.* (2019) who find herding in the period starting on April 2016 and continuing through September 2017. However, as mentioned in the Chapter 4, we can-

Table 5.3: Estimates of herd behavior in specifically chosen periods

	Dependent variable $CSAD_t$		
	Bull-year 2017	Covid-19 pandemics	Ukrainian war
Constant	5.283***	3.488***	1.678***
	(0.187)	(0.108)	(0.067)
$\lvert R_{m,t} \rvert$	0.409***	0.354***	0.232***
	(0.063)	(0.041)	(0.027)
$R^2_{m,t}$	-0.011**	0.007***	0.010***
	(0.003)	(0.001)	(0.002)
Observations	365	408	311
R^2	0.196	0.505	0.725
Adjusted R^2	0.191	0.502	0.723
Residual Std. Error	1.922 (df=362)	1.388 (df=405)	0.735 (df=308)
F Statistic	44.02*** (df=2;362)	206.20*** (df=2;405)	405.20*** (df=2;308)

Note: *p < 0.1; **p < 0.05; ***p < 0.01

not reject the non-stationarity of the dependent variable. This can impact the accuracy of the resulting model and thus readers are advised to interpret the results with discretion.

Secondly, we focus on herding in the cryptocurrency market during the Covid-19 pandemy. After its dramatic onset in the Spring 2020, the future of cryptocurrency prices was highly uncertain. During 2021, FED announced to keep rates near zero by which it turned cryptoassets into a safe haven. That meant the inflow of institutional investors as well as many households who suddenly decided to put their money in the cryptocurrency market. This course of events and its impact on markets have been studied by scholars whose conclusions yet differ. Susana *et al.* (2020) found herding behavior of three important currencies Dash, Litecoin and Cardano during the Covid-19 period, while Yarovaya *et al.* (2021), despite the increased volatility in the market, observed a decreasing herding trend. Second column in the Table 5.3 presents the results of our estimation of this matter. By studying the coefficients, we can see no evidence of intensified stress in the market, nor of herding behavior. Our result therefore takes a stand of Yarovaya *et al.* (2021) who also find no sign of imitative behavior during the Covid-19 pandemics.

Lastly, we devote out attention to studying the herding behavior attributed to the war in Ukraine. On February 24th 2022, Russian President Vladimir Putin announced a military invasion of Ukraine. The response of Western countries was unprecedented and included a number of sanctions imposed on Russia. This evoked the sense of uncertainty regarding the impacts on global economy, geopolitics and not least food and electricity security. As a result, Bitcoin price fell in that period by around 50% (CoinGecko 2023a) by which it after almost two years got closer to the pre-Covid price levels.

Arriving to results in the third column in the Table 5.3 it is worth mentioning the comparably small constant of 1.678. Therefore the usual distance between return dispersion and the market average has shrunk. Observing the coefficient related to $R^2_{m,t}$ shows the evidence of anti-herding meaning that people are staying self-reliant while making their buying or selling decisions.

To our best knowledge, this thesis is the first to study the impact of this war on the cryptocurrency market. Therefore, we would like to acknowledge that this thesis studies only the early stage of the war impact and thus should be interpreted with caution.

Summary of Periods-related Findings

To briefly recall, the evidence of herding has been found during the bull year 2017 but not during the Covid-19 pandemics and the early stage of the war in Ukraine. This findings seems to contradict the popular belief that herding behavior increases with uncertainty. It also suggests the inflow of informed investors into the market during the Covid-19 pandemics which is consistent with the increased attention from institutional investors during that period.

Moreover, the augmented value of average deviation during the Bull-year 2017 signifies increased stress in the market. This can be explained by the increased fear of "missing out" investment gains which is believed to be present in the cryptocurrency trading (Gurdgiev & Corbet 2018).

The early stage of the war in Ukraine seem not to deepen the herding behavior in the cryptocurrency market probably due to the presence of institutional investors. However, within the scope of this thesis, we cannot hope to cover all possible grounds for this finding.

5.2 The Role of Bitcoin

The purpose of this section is to examine herding around Bitcoin. By that we also investigate whether daily cryptocurrency data bring sufficiently in-dept understanding to be able to study the influence of external factors on the sample. To recall hypothesis #2, we expect Bitcoin to have significant influence on other coins in the market. Our approach will be slightly modified but still follows the main idea presented by Philippas *et al.* (2020) and Chang *et al.* (2020). Coming from Bitcoin's extraordinary performance (Urquhart 2016; Cheah & Fry 2015) and its large public awareness (Krištoufek 2015), Bitcoin's return is extracted from the sample and made a separate variable. Thus $R_{B,t}$ represents the return of Bitcoin and $R_{X,t}$ represents the market return after the Bitcoin has been removed. Observing the Table 4.1 we can notice pronounced volatility in Bitcoin returns compared to the rest of the market. We derive regression model following the Equation 3.11. In this model, negative and significant coefficient γ_2 indicates local herding while negative and significant γ_3 can be interpreted as the local market herding around Bitcoin.

In the Table 5.4, γ_2 is slightly significant and negative which suggests the local herding in the market, but in a not very persuasive way. Additionally, the significant and positive γ_3 shows the indication of anti-herding around Bitcoin which is a result in agreement with Kalinterakis & Wang (2019).

The Role of Bitcoin under Extreme Market Movements

We follow Christie & Huang (1995) to define extreme market movements that appear in 1% and 5% extreme upper and lower tails of the distribution. We test the hypothesis #2 using the extreme movements of Bitcoin. From the majority of empirical studies (Papadamou *et al.* 2021; Ballis & Drakos 2020; Kalinterakis & Wang 2019), herding is said to be pronounced during the up market, meaning that people probably fear the lost opportunity to gain money more than the loss of the money itself, or that people believe more in other's decisions and less in their own ones when the market is bullish than when it is bearish. Because we hypothesize that the cryptocurrency market contains many uniformed trades who observe primarily the price of Bitcoin when making investment decisions, we base our dummy variable D^{up} and D^{down} on the extremities in Bitcoin returns.

The results of Equation 3.12 are presented in the Table 5.5. It is worth

Table 5.4: Estimates of herd behavior around Bitcoin

	Dependent variable
	$\text{CSAD}_{X,t}$
Constant	3.095***
	(0.065)
$\lvert \text{R}_{X,t} \rvert$	0.349***
	(0.023)
$\text{R}^2_{X,t}$	-0.003*
	(0.001)
$\text{R}^2_{B,t}$	0.005***
	(0.001)
Observations	2191
R^2	0.277
Adjusted R^2	0.276
Residual Std. Error	1.882 (df = 2187)
F Statistic	279.2*** (df = 3;2187)

Note: *p < 0.1; **p < 0.05; ***p < 0.01

noticing that extreme Bitcoin movements seem not to increase the average return in the market. Moreover, under both extreme tails, D^{down} is slightly significant and negative implying that investors are perceptive to lower tail extreme movements of Bitcoin. By contrast, the coefficient D^{up} presents different behavior during extreme 1% tail and 5% tail. In the former case, its insignificance suggests no relevant influence, in the latter, the significant coefficient of -0.012 is an evidence of the increased investor collective behavior when Bitcoin return appears to be in the 1% extremity tail.

Summary of Hypothesis #2

To summarize, cryptocurrency market seems to respond to changes in Bitcoin price only moderately. Considering the market behavior when Bitcoin returns appear to be in its extremities, under 5% extreme tails herding seems to be more pronounced during the down market on contrary to the 1% extreme tails, during which herding appears stronger in the up market. Possible explanation could offer remedy through the individual perceptiveness to extreme tails.

Table 5.5: Estimates of herd behavior caused by extreme market movements of Bitcoin within 1% and 5% extreme tails

	Dependent variable $CSAD_{X,t}$	
	5%	1%
Constant	3.156***	3.127***
	(0.066)	(0.068)
$\lvert R_{X,t} \rvert$	0.290***	0.312***
	(0.025)	(0.029)
$R^2_{X,t}$	0.045*	0.001
	(0.208)	(0.002)
$R^2_{B,t}$	0.005***	0.006***
	(0.001)	(0.001)
$D^{B,up} \times R^2_{X,t}$	-0.035	-0.012**
	(0.207)	(0.004)
$D^{B,down} \times R^2_{X,t}$	-0.046*	-0.004*
	(0.207)	(0.001)
Observations	2191	2191
R^2	0.287	0.281
Adjusted R^2	0.286	0.279
Residual Std. Error	1.870 (df=2185)	1.878 (df=2185)
F Statistic	176.1*** (df=5;2185)	170.8*** (df=5;2185)

Note: *p < 0.1; **p < 0.05; ***p < 0.01

5.3 The Role of Five Dominant Cryptocurrencies

Due to the smaller than expected percipience to Bitcoin price movements, we further proceed to study the influence of five well-known major cryptocurrencies on the rest of the market. As in detail described in Section 3.3, we divide the portfolio into two subsets and study the influence of the less numerous one on the other. This, in numbers smaller subset, consists of five heavily traded currencies Bitcoin, Ethereum, XRP, Litecoin and Dogecoin. To analyze the herding behavior dependent on these five coins, we include $R^2_{BEXLD,t}$ and $CSAD_{BEXLD,t}$ to capture the dispersion and squared market return for this

Table 5.6: Estimates of herd behavior in relation to five dominant cryptocurrencies

	Dependent variable
	$\text{CSAD}_{Y,t}$
Constant	2.699***
	(0.067)
$\lvert \text{R}_{Y,t} \rvert$	0.259***
	(0.023)
$\text{R}^2_{Y,t}$	0.007***
	(0.001)
$\text{CSAD}_{BEXLD,t}$	0.374***
	(0.021)
$\text{R}^2_{BEXLD,t}$	-0.005***
	(0.001)
Observations	2191
R^2	0.371
Adjusted R^2	0.369
Residual Std. Error	1.791 (df = 2186)
F Statistic	321.8*** (df = 4;2186)

Note: *p < 0.1; **p < 0.05; ***p < 0.01

sector, labeled as *BEXLD*. Similarly, we calculate the same metrics for the remaining 95 cryptocoins adressed as sector Y. To recall, a negative and significant γ_2 implies market-wide herding, a negative and significant coefficient γ_4 indicates the herding behavior of sector Y around the sector *BEXLD* and a positive and significant γ_3 suggests that market sector *BEXLD* has a dominant influence on the market sector Y.

The results are presented in the Table 5.6. In this case, constant is smaller than in previous examples which signifies less chaos in the market without the major coins. This assertion is supported by descriptive statistics in the Table 4.1, which show significantly stronger volatility in the aggregate return of the major coins than in the rest of the market. With both coefficients attributed to squared returns being highly significant, we are sure to reject the exact linearity within the EMH. A significant and positive γ_2 shows no presence of market-wide herding. However, the negative and significant coefficient γ_4 indicates the herding behavior of sector Y around the sector $BEXLD$. In addition, we can observe a significant dominance of sector $BEXLD$ on the sector Y. In other words, we have demonstrated that the market herd around the five most pronounced cryptocurrencies and that these currencies have a dominant effect on the rest of the market in a similar way that USA has a dominant effect in the international markets.

Summary of Hypothesis #3

In summary, smaller cryptocoins seem to herd around the five major currencies. In addition, these major coins seem to feature stronger volatility in the aggregate return than the rest of the market. This suggests that traders invest in the smaller cryptocurrencies according to the information presented by the larger ones. We therefore add another piece of evidence suggesting that cryptocurrency trading does not rely on fundamental analysis.

Chapter 6

Conclusion

This thesis focuses on studying herding behavior in the cryptocurrency market between 2017 and 2022. For this purpose, the thesis uses the CSAD measure which is based on observing the cross-sectional absolute deviation of returns (Bouri *et al.* 2019; Chang *et al.* 2000). The examined period ranges from the beginning of January 2017 to the end of December 2022 and daily frequency data are used.

As a starting point, herding behavior is studied in the aggregate on the whole examined period. We find no evidence of herding behavior, nor of the contradiction of the EMH. The reason might be the length of the whole period due to which the potential non-linearities negate each other or are just not that important on the aggregate level. Therefore, on the basis of findings presented in this thesis, we cannot support the hypothesis #1.

To further contemplate this unexpected finding, we proceed by studying the asymmetric herding and the periods of special importance. Regarding the former, herding behavior is found in the up-market but not in the down market. This implies that people herd more on positive announcements which might be caused by the individual unwillingness to miss investment gains (Gurdgiev & Corbet 2018). While this topic has for a long been a controversy among many scholars, this study takes a clear stand on the "up-market" side of the debate.

Next, we dive deeper into studying the specific chosen periods in our sample. These are the year 2017, the Covid-19 pandemics and the war in Ukraine. Despite expectations, we find augmented chaotic behavior in the market only in the year 2017. This period is also the sole one displaying herding behavior. We rationalize this by the apparently higher immaturity of the cryptocurrency market in the year 2017 compared to the present. Back then, the market seemed to "grow forever" which is why it attracted many people who only mimicked the actions of their peers (Gurdiev & O'Loughlin 2020). Covid-19 pandemic and Ukrainian war regression results do not vary significantly which gives the impression of a mature market with conscious individuals. Only the constant value seems to be lower in case of the war in Ukraine which can be interpreted as the final calming down after the long-lasting Covid-19 situation.

Moving to hypothesis #2, we introduce a novel approach to study the influence of Bitcoin on the rest of the market. Due to Bitcoin's dominance among other coins and its wide awareness among general public (Urquhart 2016; Krištoufek 2015), we treat it as an exogenous variable which we expect to have a crucial influence on the herding behavior in the cryptocurrency market. Surprisingly, we find no convincing evidence of herding around Bitcoin in the market. The situation seems to be different during extreme 1% and 5% Bitcoin movements. Under the 5% extremity tails, the market appears to respond only to extremely low bitcoin returns while under 1% investors seem to herd more during the Bitcoin's high returns. One interpretation could be that people respond to any monetary value accounting for loses but the expected return needs to be sufficient to be worth the risk of investing.

Lastly, we test the hypothesis #3 by extracting five major cryptocoins (Bitcoin, Ethereum, XRP, Litecoin, Dogecoin) from the dataset and making them an exogenous market (Chang *et al.* 2020; Vidal-Tomás *et al.* 2019). This group of coins presents the largest volatility in our sample, significantly larger then that of the Bitcoin itself. Our results reveal substantial herding of the rest of the market around the major coins sector and also the major coins sector dominance on the rest of the market. Small coins thus seem to follow returns of the large giants but with the less extensive returns fluctuation.

In summary, this thesis illustrates a number of cases showing a herding behavior. The market itself seems to be maturing despite the still very pronounced influence of the most capitalizes coins. There are still many new areas to be examined and this thesis provides a nudge to some of them. The actual impact of the war in Ukraine on the cryptocurrency market represents a new matter which is open to further investigation. In continuity, studying the influence of the war in general on cryptocurrency market would be a much-needed broadening of the today's cryptocurrency literature. In addition, feel free to build on the idea presented in this thesis and add new exogenous variables. It is not unlikely that, there are several other elements influencing herding in the cryptocurrency market that can be added to the regression.

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Appendix A

Appended Table

Table A.1: Descriptive statistics B

	Variable	Mean	Med.	Min.	Max.	Std. d.	Skew.	Kurt.	ADF test
#1b	$R_{i,m}^{UP}$	1.495	0.288	0	17.829	2.315	2.277	6.620	-9.720***
	$CSAD^{UP}$	2.296	2.033	0	21.637	2.648	1.233	2.179	-7.386***
	$R_{i,m}^{DOWN}$	-1.552	0	-35.666	0	3.110	-3.864	23.559	-11.093***
	$CSAD^{DOWN}$	4.187	3.525	0	35.666	3.312	2.289	11.458	-8.838***
#1c	$R_{i,m}^{2017}$	0.842	1.238	-25.752	15.997	5.340	-0.834	2.867	-6.374***
	$CSAD^{2017}$	6.582	6.233	0	21.637	2.137	1.567	6.724	-3.072
	$R_{i,m}^{COVID}$	0.198	0.456	-35.666	10.821	3.722	-2.529	21.254	-7.594***
	$CSAD^{COVID}$	4.461	4.086	1.470	25.174	1.967	4.190	34.033	-4.926***
	$R_{i,m}^{WAR}$	-0.457	-0.147	-27.499	13.250	3.952	-1.586	8.474	-6.295***
	$CSAD^{WAR}$	2.457	2.175	0.931	16.637	1.396	4.964	38.969	-4.575***

Note: *p < 0.1; **p < 0.05; ***p < 0.01. UP (DOWN) represents the days when market is up (down). 2017, COVID and WAR refer to respective periods (see Chapter 4)