DOKUZ EYLUL UNIVERSITY

GRADUATE SCHOOL OF SOCIAL SCIENCES

DEPARTMENT OF BUSINESS ADMINISTRATION

ACCOUNTING AND FINANCE MASTER PROGRAM

MASTER'S THESIS

THE ANALYSIS OF OVERREACTION HYPOTHESIS IN CRYPTOCURRENCY MARKETS

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İZMİR – 2023

APPROVAL PAGE

DECLARATION

I hereby declare that this master's thesis titled "The Analysis of Overreaction Hypothesis in Cryptocurrency Markets" has been written by myself following the academic rules and ethical conduct. I also declare that all materials benefited in this thesis consist of the mentioned resources in the reference list. I verify all these with my honor.

Date:

23 / 07 / 2023

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ABSTRACT

Master's Thesis

The Analysis of Overreaction Hypothesis in Cryptocurrency Markets

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Aim: This research investigates the Overreaction Hypothesis in the cryptocurrency market.

Methodology: Four cryptocurrencies are taken into account to study the Overreaction Hypothesis from Aug 2017 to Aug 2022. This research aims to answer a series of questions on the number, magnitude and the type of Overreactions, the impact of COVID-19 on Overreaction and price reaction to Overreaction. Two statistical tests including one parametric and one non-parametric tests were used for statistical purposes.

Findings: The results significantly suggest that Overreactions happen in all daily, weekly, and monthly time frames. The number of Overreactions during the pandemic is significantly higher. The price of a positive Overreaction is higher than the price of a negative Overreaction for BIT during the pandemic. The change in price is higher when overreacting during the pandemic compared to that of the ordinary days. Counter reactions and price movements are happening significantly after an Overreaction. There exists a statistical consensus on the definition of return and Overreaction.

Keywords: Cryptocurrency market, Overreaction Hypothesis

ÖZET

Yüksek Lisans Tezi

Kripto Para Piyasalarında Aşırı Tepki Hipotezinin Analizi

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Amaç: Bu araştırma, kripto para piyasasındaki Aşırı Tepki Hipotezini araştırmaktadır.

Metodoloji: Ağustos 2017'den Ağustos 2022'ye kadar Aşırı Tepki Hipotezini incelemek için dört kripto para birimi dikkate alınır. Bu araştırma, Aşırı Tepkilerin sayısı, büyüklüğü ve türü, COVID-19'un Aşırı Tepki üzerindeki etkisi ve tepkiler hakkında bir dizi soruyu yanıtlamaya çalışır. İstatistiksel amaçlar için bir parametrik ve bir parametrik olmayan test olmak üzere iki istatistiksel test kullanılmıştır.

Bulgular: Sonuçlar, Aşırı Tepkilerin tüm günlük, haftalık ve aylık zaman dilimlerinde gerçekleştiğini önemli ölçüde göstermektedir. Pandemi sırasında Aşırı Tepkilerin sayısı önemli ölçüde daha yüksektir. Salgın sırasında olumlu bir Aşırı Tepkinin bedeli, olumsuz bir Aşırı Tepkinin fiyatından daha yüksektir. Pandemi döneminde aşırı tepki verildiğinde fiyattaki değişim normal günlere göre daha yüksek oluyor. Bir Aşırı Tepkiden sonra karşı tepkiler ve fiyat hareketleri önemli ölçüde gerçekleşiyor. Geri dönüşün ve Aşırı Tepkinin tanımı konusunda istatistiksel bir fikir birliği vardır.

Anahtar Kelimeler: Kripto para piyasası, Aşırı Tepki Hipotezi

THE ANALYSIS OF OVERREACTION HYPOTHESIS IN CRYPTOCURRENCY MARKETS

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ABBREVIATIONS

EMH: Efficient Market Hypothesis

CAPM: Capital Asset Pricing Model

BF: Behavioral Finance

OE: Overreaction Effect

OH: Overreaction Hypothesis

BOVESPA: "Bolsa de Valores de São Paulo" (São Paulo Stock Exchange)

BIST: Borsa Istanbul

ISE: Istanbul Stock Exchange

FOREX: Foreign Exchange Market

CPI: Consumer Price Index

PPI: Producer Price Index

ICO: Initial Coin Offering

BTC: Bitcoin

LTC: Litecoin

ETH: Ethereum

XRP: Ripple

AMH: Adaptive Market Hypothesis

FOMC: Federal Open Market Committee

PDF: Probability Density Function

CR: Counter Reaction

PM: Price Movement (In The Direction Of Overreaction)

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INTRODUCTION

Cryptocurrency, sometimes known as crypto, is a type of electronic currency that operates as a medium of exchange across a network of computers. Exchanges in this method get governed according to a decentralized approach in which all transactions get verified without the need for centralized authority. The rapid development of Bitcoin and other digital currencies since its introduction by Nakamoto (2008: 1) has led to an uprising of interest coming from governments, academics, investors, traders, and portfolio managers. Total market capitalization for crypto markets exceeded $T 1 by June 2023.

Efficient Market Hypothesis (EMH) of Fama (1970) assumes that investors evaluate stocks and other financial assets logically because they are rational beings. The argument that individuals in general, and investors specifically, are totally rational is something hard to support. Leading economists at the time, particularly Adam Smith, John Maynard Keynes, and Irving Fisher were well noted for incorporating psychological aspects of humans into their analysis from the 18th century through the first half of the 20th century. Behavioral finance seeks to understand how psychology affects investors and their behaviors in a particular market.

The cryptocurrency market is a new market that makes it possible to analyze how behavior of its participants influences asset values due to its speculative and difficult-to-value character. The bulk of cryptocurrency market participants are speculators; thus, the behavioral impact may be greater than in traditional markets (Keidan and Kelly, 2017: 23).

One of the financial market abnormalities that has been the most thoroughly studied is overreaction (Ball, 2009: 10). Only a few research, to our knowledge, have specifically addressed the overreaction in the cryptocurrency market. An overreaction is typically defined in empirical literature as a significant price change. The results of current empirical research are challenging to compare with one another since they use

a range of modeling techniques and external factors, and they depend primarily on the choice of related elements.

METHODOLOGY

The data for four cryptocurrencies were taken into account from Aug 2017 to Aug 2022. These cryptocurrencies include BIT, LIT, ETH, and XRP. This research aims to answer a series of questions on the number, magnitude and the type of Overreactions, the impact of COVID-19 on Overreaction. Two statistical tests including one parametric and one non-parametric tests were used for statistical purposes.

RESEARCH QUESTIONS

In this study we want to answer a series of research questions as follows:

- How the number, magnitude, and the type of Overreactions change in the market?
- How is the Overreaction stressed by the COVID-19 pandemic?
- Is there a statistical consensus on the definition of an Overreaction?

FINDINGS

The results significantly suggest that Overreactions happen in all daily, weekly, and monthly time points. The existence of price overreactions indicates that the cryptocurrency market is not efficient, which allows investors and portfolio managers to take advantage of price overreactions.

The number of Overreactions during the pandemic is significantly higher. The price of a positive Overreaction is higher than the price of a negative Overreaction for BIT during the pandemic. The change in price is higher when overreacting during the pandemic compared to that of the ordinary days.

Results suggest that both counter reactions and price movements in the direction of overreaction, happen more intensely after an Overreaction occurred. There also exists a statistical consensus on the definition of return and Overreaction.

CONTRIBUTIONS

- We observed that the number of positive Overreactions was slightly greater than the number of negative Overreactions; however, this finding was not statistically significant
- Current study examines the overreaction behavior of four cryptocurrencies with a focus on the COVID-19 pandemic's effects
- During the Covid-19 epidemic, overreactions occur more often and with greater intensity
- We showed that the prevalence of the overreaction is not subject to the time frame and the number of Overreactions under different time points is proportionally distributed
- We also found that the price for positive Overreactions is higher than the price for negative Overreactions for BIT during the pandemic
- Since there is no consensus on the definition of an Overreaction, we used a definition based on High-Low prices alongside Close-Open prices.
- We later implemented two statistical tests to compare the performance of the two formulas used to define an Overreaction.
- Both tests significantly confirm that both formulas can be safely used to study the Overreaction effect.

1 CHAPTER I: THE CONCEPTS OF CRYPTOCURRENCIES

"Mathematics is never going to lead you to a higher truth," said John Nash in *A Beautiful Mind*. Although this seems far from reality, it is one of the magnificent quotes some people keep in their minds when facing complex situations in their lives. Some prefer to put personal characteristics such as fear and greed when trying to solve problems that stem from their daily routines. This results in different behaviors against the same problem. One of the concepts originating from such a belief is the overreaction to various concepts, especially the economical ones.

The global economy was significantly impacted by the COVID-19 pandemic. This includes a considerable number of lay-offs and bankruptcies all over the world. One of these impacts was significant droppings in financial markets which highly affected mankind's life leading it to a point with ambiguous outcomes. Surprisingly, even powerful countries could not act efficiently on this and completely lacked control of specific stock markets. It was when many abnormal returns were observed in various markets.

This chapter will depict a decent introduction to cryptocurrencies and their properties. This chapter will be concluded by presenting the main research questions together with the structure of this thesis.

1.1 CRYPTOCURRENCY

Cryptocurrency, sometimes known as crypto, is a type of electronic currency that operates as a medium of exchange across a network of computers. Exchanges in this method get governed according to a decentralized approach in which all transactions get verified without the need for centralized authority. The original concept of cryptocurrencies was developed by American cryptographer David Chaum in 1983. He termed it ecash, and it was later realized as DigiCash in 1995.The

interesting idea was that a third party cannot trace the digital currency transited in this method. However, *ecash* does not provide sellers anonymity. As soon as they receive coins, they must return them so that the bank is aware of their earnings, timing, and other information. The primary issue with *ecash* was that getting banks and retailers to use it was difficult. Users did not desire *ecash* because there were not many businesses that accepted it. Its lack of support for user-to-user transactions was far worse. The user-to-merchant transaction was the main focus. Note that Bitcoin supports both user-to-user and user-to-merchant transactions (Ammous, 2018: 11).

It was around 2009 when Satoshi Nakamoto created Bitcoin based on a cryptographic hash function. Later many other cryptocurrencies were developed using the same scheme. Currency holders built a network of transactions that get recorded in a blockchain. Besides this, solving difficult mathematical problems using computer power results in generating coins. Coins can be sold and purchased in the network that is stored and spent in a cryptographic wallet. The wild development of the cryptocurrency market has provided a unique opportunity to study its trend and evolution. The availability of data for the crypto market allows for employing various mathematical and statistical approaches from its birth to the present day. This results in identifying important characteristics associated with this market (Ammous, 2018: 23).

Bitcoin depends on miners since they verify each transaction, create, and store every block, and decide which blocks to add to the blockchain. Additionally, it has been seen that miners are rewarded for their efforts. The Bitcoin network benefits from and depends on several functions, such as validating transactions and blocks. The fact that the Bitcoin protocol needs miners in the first place is due to these tasks. The competition to find blocks and make money, while not vital to the Bitcoin network itself, is meant to encourage miners to complete the necessary tasks. The Bitcoin protocol creates new coins with each block that is verified, and these coins are awarded to the miner as compensation for their time and effort (Caetano, 2015: 122).

1.2 THE NEED FOR CRYPTO MARKETS

Assume person A borrows money in the form of cash from person B. There is a possibility that this amount will not get back to person B. This possibility originates from the fact that procedures taken by banks and financial institutions do not completely fulfill encryption and security standards which leaves the probability that person B will not be able to get his money back. Now consider a poor financial network where people invest their money and trade their stocks. This problem exists to some extent when dealing with credit cards too. This together with problems related to the cash and credit system leaves the attention for having direct control over transactions by users involved in the process. The development of decentralized systems and the theory of blockchain provided the possibility of such a control that solves the shortcomings of centralized systems to a substantial extent. However, one should not neglect the benefits of the cash system including its better anonymity and the possibility of conducting offline transactions with no interference from a third party (Caetano, 2015: 142).

Bitcoin does not possess inherent value like gold, as should be highlighted. In all these conceptions, the value of digital money is intrinsically related to either the dollar or a commodity. The digital money assets' value will fluctuate based on how much the dollar changes in value. The use of gold or diamonds as a basis for money is a result of scarcity. Designing the system so that creating money requires solving a computational challenge that takes some time to solve is one technique to create scarcity in the digital world. This concept is put into practice by bitcoin mining. The blockchain, a secured ledger in which all Bitcoin transactions are securely recorded, is another essential element of Bitcoin. In essence, Bitcoin merges the concept of secure timestamping to record a ledger of transactions and avoid duplicate spending with the idea of employing difficult mathematical problems to control the formation of new currency units. The public blockchain is accessible for observation by anybody, making it susceptible to assaults. Bitcoin has a system to automatically alter the problem difficulty repeatedly because the hardware has a tendency to become significantly less expensive over time for a specified amount of computer power. The

blockchain and decentralized architecture that permits user-to-user transactions are only two of the major breakthroughs in Bitcoin (Caetano, 2015: 154).

1.3 DECENTRALIZATION IN CRYPTO MARKETS

In crypto markets, one does not require to be given a username in order to register as a user in a system without a central authority. The pattern of one's behavior may lead to her identification even if she does not clearly and explicitly register or give her actual identity while using Bitcoin. There is not all, or nothing approach to decentralization. Nearly no system is entirely centralized or decentralized. Although the protocol used by Bitcoin has a decentralized nature, services like Bitcoin exchanges, where users may exchange bitcoins for a variety of currencies, and wallet programs, which allow clients to control their digital currencies, may be centralized or decentralized to a greater or lesser extent. (Gencer et al., 2018: 19).

1.4 HOW BITCOINS GET EXCHANGED?

The way bitcoin gets exchanged is a lot like how banks operate, especially regarding the user interface. Like a bank, they promise to return any deposits of bitcoins upon request. One can perform several banking-like tasks on the exchange. They search for clients who are prepared to take opposing sides in a transaction. By merely collecting fees, cryptocurrency exchanges can serve as market makers, or they can operate as an integrating platform through the use of the spread between bids and offers as a kind of charge. (Caetano, 2015: 128).

It is crucial to keep in mind that no transaction takes place on the Bitcoin blockchain when a transaction occurs. Transferring bitcoins or dollars from one account to another can be done without accessing the blockchain by the exchange. The only thing that changes as a result of this exchange is the promise that was already made to the user. Using exchanges has advantages and disadvantages. Exchanges make it simple to transfer value back and forth between the fiat currency market and Bitcoin. Risk is the drawback of this process. In comparison to other industry sectors,

the exchanges sector includes the most operational units and the most employees. Wallet and exchange boundaries are becoming hazier and hazier (Caetano, 2015: 242).

1.5 CRIME AND CAPITAL CONTROL IN CRYPTO MARKETS

Control of capital includes regulations or laws that are in place in a nation and intended to restrict the flow of capital (money and other assets) into or out of that country. One can easily purchase bitcoins with local money, send those bitcoins electronically outside the country, and then exchange them for money or other assets. That would enable them to export money or wealth without interference from the government or import it in the opposite direction. Governments may be concerned about untraceable digital currency because it facilitates certain types of criminal activity such as kidnapping and extortion. Silk Road, a secret dark-net marketplace, allowed for the distribution of prohibited goods to almost one million members and several hundred drug dealers. Given that people want to see lawbreakers punished, legitimate individuals view Bitcoin's semi-anonymity characteristic unfavorably. (Caetano, 2015: 293).

1.6 CRYPTOCURRENCY MARKETS

Websites such as coinbase.com display the bitcoin exchange rate for different fiat currencies on various exchanges in the bitcoin world. The prevailing consensus is that national government actions or limits will not cause inflation for bitcoin and other cryptocurrencies. Millions of dollars travel through this large market every day. Prior to the end of 2015, the European Court of Justice determined that VAT (value-added tax) was not applied to transactions made using Bitcoin. (Hileman, 2016). The circulation of bitcoins will be significantly improved by these kinds of steps. It is sufficiently large to establish a consensus price, even if it is not on the same level as the New York Stock Exchange or the EURO/DOLLAR market, which are considerably larger. In this market, like in any other liquid market, supply and demand determine the consensus price. The price will be determined by this market mechanism

at a level that balances supply and demand. It should be stressed that a drawback of cryptocurrencies is their propensity to be traded like commodities (Caetano, 2015: 311).

1.7 THE IMPORTANCE OF BITCOIN

A considerable number of people are enthusiastic about Bitcoin. A big advantage over conventional currencies that Bitcoin offers is its quick transactions between users, especially where there are multiple foreign businesses involved. While some people are enthusiastic about its potential business applications, others are more interested in the social and political ramifications. Regarding the first two, reasonable people may disagree, but Bitcoin is an advanced technology that is innovative, intriguing, and founded on strong principles. Market capitalization, the anticipated number of users, and the daily transaction volume are the three key metrics for success in the cryptocurrency industry. Concerns include the likelihood of fraudulent activity, the extremely volatile nature of the Bitcoin price, the danger of settlement, the potential for the evasion of taxes, security issues, and prior insolvency.

Besides Bitcoin, other important concepts are now getting explored. Some of these ideas may one day be more significant than Bitcoin itself. Smart contracts are a possible application for the blockchain technology that drives Bitcoin (Hileman, 2015: 92). The preprogrammed payments under these contracts are made in response to the fulfillment of certain requirements. Cryptography was used to generate a digital asset called cryptocurrency. Cryptocurrency rivals are also working to offer a substitute for digital money. In order to allow customers to use their goods for charging debit or credit cards associated with their accounts, they are making use of their infrastructure and technology.

The rational expectation of upcoming dividends which is discounted by the required return forms the main framework for pricing a particular asset. The level of required return is higher for riskier stocks because of being more influenced by movements in the market. As shown by Campbell and Shiller (1988: 668), While there are times when stock prices are high, overall stock market returns are often poor. This,

however, is in contradiction with the assumption of time-invariancy. Additionally, evidence shows that there is a low average return rate for high market-to-book stocks (Fama and French 1993: 42). This brings the idea of market predictability. In addition to this, required returns are subject to the risk preference of investors and they might act differently on the same stock when exposed to different risk levels (Bansal and Yaron, 2004: 1493). However, mearing the exact level of risk and controlling for change in risk preferences is something hard to control and has remained a black box for decades.

1.8 THE RESEARCH INQUIRY

In this study, we want to investigate the Overreaction Hypothesis in crypto currency markets. Cryptocurrency is a type of stock with a striking market that is likely to inherit special characteristics of ordinary stock markets. This includes the Overreaction Effect in which its evidence has been verified in specific stock markets as will be reviewed in the next chapters. Additionally, we want to study the structural properties of the possible Overreaction Effect in crypto markets.

1.9 STRUCTURE OF THIS RESEARCH

Chapter 2 of this research will delve into the theoretical background of the Efficient Market Hypothesis, behavioral finance, and behavioral biases. Chapter 3 will review the literature on EMH and behavioral biases specifically on the Cryptocurrency market. Chapter 4 will talk about the data and methodology we have implemented. Finally, chapter 5 will discuss the results concluding the main findings of this study.

2 CHAPTER II: THEORETICAL BACKGROUND

In this chapter, we will be discussing some important concepts about the structure of financial markets including both stock and cryptocurrency markets.

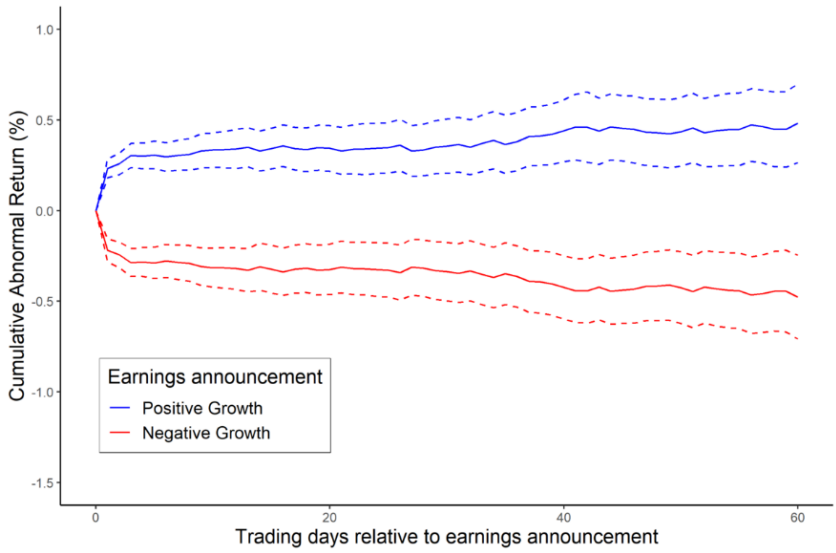
2.1 EFFICIENT MARKET HYPOTHESIS

There was a belief against the idea that the market of securities was efficient meaning that they truly reflect information about stocks (Fama, 1970: 413). In other words, when new information enters a stock market, news gets incorporated into the stock prices with almost no delay. Therefore, neither technical nor fundamental analysis can help investors to select "undervalued" stocks. This means that no one can achieve more than what s/he can obtain by selecting a set of randomly selected portfolios of stocks. This is generally known as Efficient Market Hypothesis (EMH). According to Fama (1970: 414), the EMH in standard finance theory identifies the traits of efficient financial markets. Asset prices are erratic according to previous prices and the volume of trading data in the weak form of the EMH. The theoretical justification for equity behavior is thus significantly affected by any indication of a time-series dependency in equity data. Due to a wealth of research using different methodologies, there is substantial literature on the subject.

An efficient market hypothesis is described in such a way that the values of securities always accurately reflect the data available (Fama, 1970: 402). Simply said, a normal investor is not likely to consistently beat the market. As a result, the significant energy that such investors expend in studying, choosing, and trading equities are pointless. Within a decade of its development in the 1960s, the EMH witnessed enormous empirical and theoretical success. In fact, the EMH and its applications formed the foundation for academic finance in general. The EMH has the strongest empirical support of any economics hypothesis, according to research (Fama 1970: 412).

EMH first assumes that investors evaluate stocks logically because they are rational beings. Second, because some investors lack rationality, their trades cancel one another out without altering prices because they are random according to some fundamental probability laws. Third, investors that act irrationally are neutralized by those who arbitrage in the market that are offsetting their influence on pricing. Investors who use reasonable judgment will evaluate each investment according to its fundamental value, which is the discounted net present value of its anticipated future cash flows. Once investors discover something about the underlying values of assets, they respond quickly to the most recent information by rapidly increasing prices in reaction to good news and dropping them in reaction to bad news. As a result, security prices often assimilate new information rapidly and adjust to reflect revised net present values of cash flows. Thus, the EMH is primarily an outcome of equilibrium in markets that are competitive and include fully rational investors. As Figure 2-1 shows, it is challenging for investors to exploit information regarding earnings to generate abnormal returns since it is rapidly disclosed. (Ball and Brown, 1968: 173).

Figure 2-1: Cumulative abnormal returns in the presence of positive and negative growth.



Source: Retrieved from *mdpi.com.*

The idea behind EMH is very much like the random walk in the literature of stochastic processes. According to the structure of a random walk, the stock's today

price solely relies on the news and information on that day and is independent of the price of the same stock yesterday. This conveys the concept of unpredictability, meaning that stock prices cannot be predicted. In other words, an uninformed buyer new to a market is expected to get at a return as an experienced person gets in the same market.

2.1.1 Types of EMH

2.1.1.1 Weak Form

Historical prices and returns are important stale data. The weak type of EMH states that larger risk-adjusted earnings cannot be produced using previous price and return data. Predictions for the future cannot be made using technical analysis, and it does not allow investors to gain greater benefits, as said by weak form (Malkiel, 1989: 131).

2.1.1.2 Semi-Strong Form

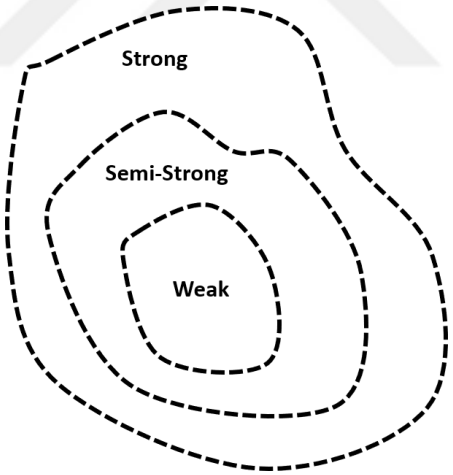
No publicly available knowledge can help investors generate better risk-adjusted returns according to semi-strong form. Or, to put it another way, knowledge that becomes public is promptly reflected in the price, thus an investor will not benefit from utilizing such data to estimate returns. Trading on the knowledge that other market players already know cannot reward investors. It is still conceivable for an investor to make anomalous risk-adjusted returns using some sort of data known as inside information which is not accessible to the public (Malkiel, 1989: 131).

2.1.1.3 Strong Form

Because insider information swiftly leaks out and is factored into prices, the EMH strong form claims that even these profits are unachievable. Sincerely, weak, and semi-strong form efficiency has been the focus of the majority of EMH analyses rather than adopting the extreme stance that successful insider trading does not exist. There is additional systematic proof that insiders generate some abnormal gains even when they act in entirely legal ways (Seyhun, 1998: 174; Jeng et al., 1999: 82).

In conclusion, Under the semi-strong form, "information" refers to all publicly accessible information; under the weak form, "information" refers to past prices; and "information" refers to all publicly accessible and unavailable information that affects asset value under the strong form. Figure 2-2 shows how different forms of EMH interact.

Figure 2-2: Different forms of EMH where Weak form is a particular instance of Semi-Strong form, which is a particular instance of Strong form.



Source: Retrieved from Seyhun (1998: 173).

2.1.2 Empirical Foundations for EMH

The neoclassical financial period started in the early 1950s, at the same time that Markowitz released his portfolio optimization theory. After that, the capital structure irrelevance theorem was developed by Modigliani and Miller (1958: 294). Sharpe

(1964: 240) and Lintner (1965: 612) created asset pricing models, namely the CAPM, while Fama (1965: 413) established the conditions for different kinds of market efficiency and extended the efficient market hypothesis. Black and Scholes (1973: 651) generated the option pricing theory in the decade of the 1970s. The EMH's empirical predictions can be classified into two categories. First of all, a security's price ought to react to new information about it as soon as it is made available to the market and should do so properly. This implies that others who learn of the news later—for example, by reading it in company reports or newspapers—should not be able to take advantage of it. It also implies that price changes in response to news should, on average, be correct. Prices should not under or overreact to specific news items. After the news' initial impact, there should not be any price movements or reversals. Additionally, prices should not fluctuate in the absence of new information regarding the security's value because a security's price must correspond to its value. In other words, prices should not alter in response to shifts in a security's supply or demand that do not come with information about its underlying value (Titan, 2015: 446).

The main conclusion that follows from pricing responding quickly and accurately to new information is that outdated information is useless for generating profits (Fama, 1970: 403). Every time researchers have discovered a profitable opportunity brought on by trading stale data, adversaries have been quick to offer a model of risk—convincing or not—that would lower these earnings to a reasonable reward for taking risks. Moreover, the results of autocorrelation studies aimed to show that the random walk theory was supported by American stock prices (Lee, 1992: 324).

2.1.3 Findings Against the EMH

The practical problems with the EMH have emerged earlier than the theoretical ones. Stock market prices fluctuate much more than could be explained by a straightforward model in which these prices are identical to the predicted net present value of future dividends, according to Shiller's (1981: 122) research on stock market volatility. Extreme losers and extreme winners are the two kinds of companies that De Bondt and Thaler (1985: 803) compare in terms of performance. Stock markets

overreact: the extreme losers have been too cheap and, on average, recover throughout the next period, whereas the extreme winners have gotten too expensive and provide lower subsequent returns. Momentum (Jegadeesh and Titman 1993: 88), which demonstrates that changes in the prices of particular stocks over a six- to twelve-month period tend to forecast future changes in the same direction. Short-term tendencies persist, in contrast to the long-term trends noted by De Bondt and Thaler, which frequently reverse.

Recent years witnessed considerable empirical difficulties for even the weak form efficient markets hypothesis. Even Fama (1991: 413) concedes that stock returns can be predicted based on previous returns, contradicting the findings of the preceding studies. In periods of speculative bubbles and collapses, such as the 1920s and the consequent Great Depression, the dot-com boom and crash of 2000–2003, and the subprime bubble and catastrophic financial crisis of 2007–2008, the biggest deviations take place. The fact that historically smaller stocks have outperformed large stocks in terms of returns is likely the most well-known divergence from the semi-strong form. Additionally, the better return from small stocks has historically been concentrated around January of each year. There is no proof that small stocks are any riskier in January. Many sudden price changes in stocks do not seem to correspond with important news. Cutler et al. (1991: 544) examined the 50 biggest one-day stock price changes in the United States after World War II and discovered that many of them occurred on days with almost no significant announcements. For instance, on Monday, October 19, there was no obvious news, and the Dow Jones Industrial Average dropped by 22.6 percent.

Richard Roll has conducted two eye-catching experiments that both come to the same conclusion (1984, 1988). The majority of scenarios do not call for effective financial markets. Larger bid-ask spreads, biases, and inefficiencies exist in emerging markets. Although on a lesser scale than in many other countries, modern markets in the industrialized world nonetheless exhibit biases and inefficiencies. There would not be a need to reward investors more generously than in developed markets if there was not any ongoing instability or unpredictability in emerging economies.

In terms of Morocco, Egypt, Jordan, and Turkey, Ball (2009: 48) investigated four different marketplaces between 1997 and 2002. Using semi-parametric tests, he concluded that these markets were not efficient. Malkiel et al. (1999: 451) examine the application of behavioral finance to forecast price changes. The authors investigate the performance of large-cap companies traded on the Athens Stock Exchange in Greece from 1995 to 2005 to see whether combining technical analysis with behavioral finance might result in successful trading techniques. In order to forecast future stock values, the authors used short- and long-term moving averages. The authors concluded that the approach was "very profitable" and thus supported the existence of behavioral phenomena at the Athens Stock Exchange.

According to the efficient market theory, investors cannot continuously make abnormal returns by trading using past data. Technical analysis is still relevant today and trade volume is nearly 60% more than usual when head-and-shoulders patterns are visible. They conclude that technical analysis overall greatly increases noise trading. The two types of traders are irrational (noise) traders and information consumers (rational or information traders), depending on their level of rationality. Investors that do not trade based on the information are known as noise traders, according to Black (1986: 537). A considerable amount of empirical evidence demonstrates that noise traders engage in speculation (De Long et al., 1990: 735), hedging (Dow and Gorton, 1994: 846), and liquidity trading (Dow and Gorton, 1993: 644; Foster and Viswanathan, 1990: 621; Pagano and Roell, 1996: 606). According to Swaminathan (2000: 290), traders can profit from momentum tactics by short-selling underperforming equities while concurrently purchasing well-performing stocks. In 1985: 803, De Bondt and Thaler became the first to propose the idea of contrarian profit. They argue that inexperienced investors focus primarily on the latest information and less on historical information which leads them to overreact and also to earn contrarian profit that refutes the EMH.

The argument that individuals in general, and investors specifically, are totally rational is something hard to support. Many investors construct their demand for assets based on superficially irrelevant information. According to Fischer Black's words (1986: 132), they trade on noise rather than information. Investors buy and sell actively and expensively managed mutual funds, follow stock price trends, and adhere to other

popular models while failing to diversify, buy, and sell based on financial experts' advice, actively trading stocks, and churning their portfolios. Investors also sell winning equities while holding onto loser ones, raising their tax obligations.

The principles of economic rationality are frequently and consistently violated by investors. People diverge from the typical decision-making model in a variety of ways, as stated by Kahneman and Riepe (1998: 73). Loss aversion, or the well-known unwillingness of investors to sell stocks when they decline in value (Odean, 1998: 1931). A stronger loss function than a gain function is referred to as loss aversion first outlined and modeled by Kahneman and Tversky (1979: 156) in their "Prospect Theory". Another is the equity premium puzzle, which is investors' general reluctance to hold equities (Mehra and Prescott, 1985: 158; Benartzi and Thaler 1995: 88). When making predictions about uncertain events, people consistently deviate from the Bayes rule and other principles of probability theory (Kahneman and Tversky, 1973: 119). For instance, investors may extend the near-term histories of some companies' quick earnings growth too far into the future, overpricing these businesses as a result. As past growth rates do not achieve again, such overreaction reduces future gains.

Heuristic-based beliefs, as opposed to Bayesian rationality, are frequently referred to as "investor sentiment." Investors whose behavior deviates from the normative model are labeled as "unsophisticated" or, in the words of Kyle (1985: 1335) and Black (1986: 540), "noise traders." Instead of uncorrelated random errors, investor sentiment represents frequent judgment mistakes made by a large number of investors. To reduce the risk of falling short of the benchmark they are measured against, such as the S&P 500 Index, professional managers may select portfolios that are overly close to it. To avoid falling behind and appearing undesirable, they could also herd and select stocks that other managers choose (Scharfstein and Stein, 1990: 478). On aggregate, managers of mutual funds and pension programs perform worse than passive investment strategies (Ippolito, 1989: 21; Lakonishok et al., 1992: 40). Even if sentiment is connected among novice investors, arbitrageurs—who may not be susceptible to psychological biases—should take the opposite side of inexperienced demand and return prices to their fundamental levels. The existence of comparable alternatives for securities whose price is possibly impacted by noise trading is vital to the achievement of arbitrage. Securities typically have no clear alternatives. As a

result, arbitrage does not aid in determining the fundamental price levels of, for example, stocks and bonds (Figlewski, 1979: 85; Campbell and Kyle 1993: 31).

In finance, arbitrage is defined as "the simultaneous purchase and selling of the same, or substantially similar, security in two different marketplaces at advantageously different prices" (Sharpe and Alexander 1999: 121). According to Mandelbrot (1971: 234), commodities, stocks, bonds, and derivatives must all be traded at their fair value in a competitive financial market. Any new information will inevitably lead to discrepancies, but these should be resolved right away. Even in situations when some investors are not completely rational, the arbitrage process aligns security prices with their fundamental values. The competition for higher rewards among arbitrageurs ensures that prices quickly respond to fundamental values. In the end, it is unclear if rational arbitrageurs are taking money away from irrational investors.

Even though the two securities are basically the same, the pricey security may increase in price while the inexpensive security may decrease in price. This form of risk, known as "noise trader risk," by De Long et al. (1990a: 734), demonstrates that even an arbitrage that appears to be almost flawless from the highly dangerous and hence likely to be limited. This subject is thoroughly discussed in the important article "The limitations of arbitrage" by Shleifer and Vishny published in 1997. The authors highlight how arbitrageurs are unable to repair inefficient prices due to a lack of money, agency issues, and other limitations.

2.2 BEHAVIORAL FINANCE

The well-established assumption underlying the EMH is Behavioral Finance (BF). BF seeks to understand how psychology affects investors and their behaviors in a particular market. The Nobel prize receiver Richard Thaler was awarded the prize for his contribution to behavioral economics.

The decision-making process might not be in line with Von Neumann-Morgenstern's expected utility theory indicating that rational decision-making gets constrained under specific conditions. Cognitive psychology and rational boundedness

are two important components when dealing with behavioral finance. A part of irrational decision makings and systematic errors is subject to factors such as overconfidence, conflicting preferences, and putting more weight on recent experiences which are heavily discussed in the literature of cognitive psychology. The other part of this issue is because of limits to arbitrage. For example, loss-averse individuals might feel worse when losing $1 compared to gaining 1.5$. This arises from the fact that beliefs are not fully Bayesian. There are two major differences when pointing out EMH and BF. When EMH assumes investors are irrational, it does not assume the market is irrational and it does indeed assume the market can make unbiased predictions for the future. However, BF can potentially assume the market is inefficient under specific conditions.

How plausible is the EMH's claim that everyone makes decisions in a totally rational way? Leading economists at the time, particularly Adam Smith, John Maynard Keynes, and Irving Fisher were well noted for incorporating psychological aspects of humans into their analysis from the 18th century through the first half of the 20th century. One of the first insights was provided by Selden (1912: 92), who proposed that stock price fluctuations were critically influenced by the mindset of market participants decades before behavioral finance emerged as a school of thought. The concepts of rationalism, an efficient market, and maximization of profit are frequently the foundations of conventional financial theories (Fama, 1970: 412). These theories concentrate on objective market conditions, but they frequently fall short of addressing irregular and abnormal market behaviors. People are normal in behavioral finance, according to Statman (1999: 42), but they are rational in standard finance.

Decision-making is the starting point for behavioral finance. It integrates ideas from the fields of classical economics, finance, and psychology and aims to suggest a fresh way of approaching conventional financial theories. To explain numerous anomalous consequences, like overreaction, underreaction, overconfidence, group behavior, the creation of economic bubbles, the excessive volatility of the stock market, and many others, some academics have suggested psychological and behavioral decision-making theories.

Financial economics specialists have all agreed on this presumption, and it has never been substantially criticized or disputed. In the 1980s, facts from the stock market and laboratory tests started to show up that such an assumption would not always be true (Levy and Levy, 2002: 1344; Barberis et al., 2001: 48). Investors frequently act irrationally while making dubious investment choices. Indications of such a tendency have triggered a significant debate in the field of financial economics, engaging many outstanding academics in the discussion and encouraging them to initiate studies in this field. (Brav and Heaton, 2002: 603; Coleman, 2007: 68). A new field of study called behavioral finance has emerged as a result of this.

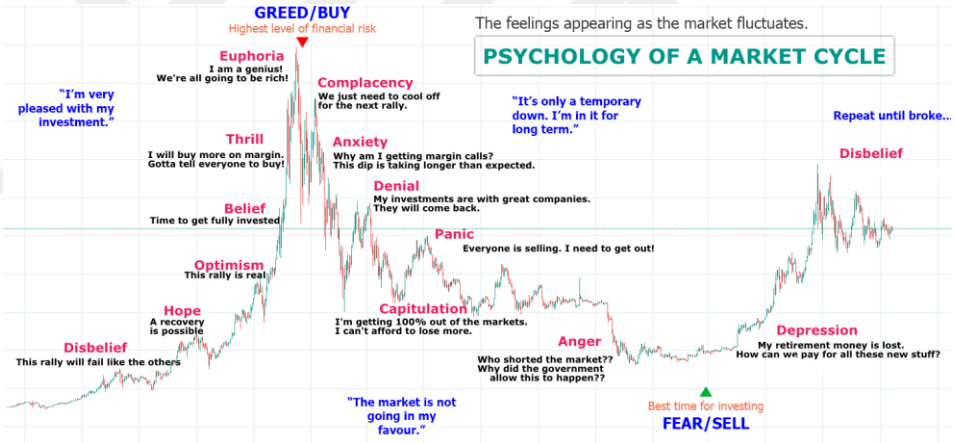
First, various "anomalies" were reported by specialists. The collection of empirical data that is difficult to explain with the rational paradigm is one of the factors contributing to the expansion of behavioral economics over the past few decades. Second, a new set of models was created using more psychologically sensible presumptions. Third, they developed strategies for assisting individuals in making better financial choices. Prospect theory, created by Daniel Kahneman and Amos Tversky, was a major influence on the development of behavioral economics. It is interesting to note that Kahneman and Tversky, both psychologists, had little to no experience with traditional finance. But since it tries to represent how individuals actually make decisions rather than merely depending on the utility decision-making techniques that built up finance theory, prospect theory has proven valuable to economics. In order to adapt prospect theory to financial markets, Richard Thaler, who was already a finance scientist at the time, incorporated the economic and finance theory.

Richard Thaler was a key figure in the development of behavioral economics, notably in its early years. First, he identified several abnormalities and constantly stressed them, most notably in a series of articles published in the Journal of Economic Perspectives. The fundamental goal of behavioral finance is to spot and explain market inefficiencies and mispricing. No article illustrates this as effectively as Lamont and Thaler's (2003: 804) groundbreaking work. Second, he started the process of developing new models that were more psychologically reliable, and the most recent models still rely on a number of the interpretations he first outlined decades ago. Third, he pioneered the search for ways to influence people's investment choices, most

notably by advocating for higher saving rates in US retirement plans. Fourth, he served as the main instructor for the behavioral economic experts who came after him.

The phenomenon of stock market bubbles is one that behavioral finance has indeed been notably good at explaining. Shiller (1998: 422) predicted a significant drop in stock values that came to be recognized as the tech bubble using the conceptual basis of behavioral finance. Since the EMH contends that valuation ratios cannot forecast future price movements Shiller's use of the Dividend/Price and P/E ratios significantly chipped away at the EMH's supports. The psychology behind a market cycle can be seen in Figure 2-3 (Kamstra, 2003: 337).

Figure 2-3: The Psychology of the market cycle. This graph shows how investors feel at different times when they want to invest in a stock.



Source: Retrieved from Kamstra (2003: 337).

2.2.1 Bubbles

Investors in a stock market sometimes increase prices higher than their actual value. This happens for several reasons such as stock valuation. This is a type of economic bubble which is called a stock market bubble. From the perspective of BF, this happens because of cognitive biases that lead to groupthink and herd behavior. It should be noted that this happens in all types of markets even those which are somehow

predictable. Beside this perspective, many see the stock market bubble as rational, intrinsic, and contagious. Creating a bubble in financial markets has always attracted much interest, not only from an academic perspective but also for practitioners and policymakers who attempted to dampen the negative impacts of price fluctuations.

The fast inflation in a bubble causes a quick reduction in value which is sometimes called a "bubble burst." When a bubble happens the assets get typically traded at a price that surpasses the intrinsic value of the asset. Still, there is a debate on the cause of bubbles and some economists do not believe bubbles even occur. However, bubbles get investigated after a huge drop occurs in prices. Some economists also believe that there is an association between the occurrence of a bubble and investor behavior.

2.3 BIASES

Because not everyone can imaginably have and invest based on the same set of data, behavioral finance was born. Each person will check and notice various things, and each individual will have a distinct perspective on what they see. Because various personalities have varied decision-making processes, personality traits play a crucial role in investing decision-making. Santos and Rosati (2015: 344) conducted a literature analysis on the history of decision-making and discovered that humans in the contemporary complicated society make decisions based on behavioral biases. The goal of behavioral finance is to better understand the psychological and sociological factors that affect how individuals and institutions make investment decisions. According to behavioral finance, a variety of behavioral biases influence how investors make investing decisions, driving them to depart from rationality and make irrational choices (Niehaus and Shrider, 2014: 695). Decision-making involves gathering information, assessing the options, and selecting one specific alternative among a large number of choices.

Findings show that individual investors are less competent and more susceptible to psychological biases. There is solid proof and justification for the notion of bounded rationality that suggests people do not always have access to all the necessary

knowledge to make the best decisions (Kinoshita, Suzuki, and Shimokawa, 2013: 1999). Decisions made by individuals are either entirely irrational or partially rational. This idea demonstrated that people have cognitive biases and restrictions that prevent them from making fully rational decisions (Ahmad Zamri, et al., 2017: 600). Numerous research has revealed investor behavioral biases, which are inconsistent with the efficient market theory (Musciotto et al., 2018: 44). Anagol and Gamble (2013: 298) studied how equity allocation is impacted by performance presentation. The authors invited participants to allocate the future after providing them with information about how investments had performed in the past as part of their experiment. It explicitly refutes the concept of complete rationality. Dividend yield can be quite crucial to some investors when choosing mutual funds, much like past performance or total costs. Due to investors' skewed tendency to choose high dividend yields, some mutual funds have developed a juicing technique that raises trading expenses, taxes, and returns.

2.3.1 Heuristic Behavior

Patrick and Charles (2011: 193) pointed out that when faced with uncertainty, people frequently rely on heuristics or rules of thumb instead of rational reasoning. Heuristics are a type of rule of thumb used to find quick solutions to difficult issues (Barberis and Thaler, 2003: 1124). Investors often make decisions under dangerous and complex circumstances relying on mental shortcuts rather than gathering and rationally evaluating all relevant information (Uygur and Tas, 2014: 237).

2.3.1.1 Anchoring

Upcoming interest rates that are implicitly predicted based on existing rates are just too close to the starting point (the anchor) that is utilized to base predictions. Investors do not base their selections on a fundamental basis. Instead, they frequently make decisions according to the price at which the first or final investment in a stock was acquired. The anchor, which drives irrational choices, is this purchasing price. The

investor thinks the new price is reasonable compared to the purchase price. Anchoring affects individual decisions since investors are unaware of the information's presentational style. People appear to be impacted by random data while making judgments, even if they are aware that the data has no meaning and significance or is abnormally high or low. One of the most extensively studied psychological biases is anchoring (Shin and Park, 2018: 991). Additionally, Tversky and Kahneman (1974: 1128) discovered that people frequently feel restricted by an "initial anchor". When making judgments, the common individual tends to heavily rely on the earliest set of information, which is known as anchoring (Shin and Park, 2018). Researchers have found that anchoring has an adverse effect on traders' or ordinary individuals' investment decisions (Ahmad and Ali Shah, 2018: 224). Thus, the heuristic bias known as anchoring leads investors to place too much weight on recent market fluctuations and pricing (Ormos and Timotity, 2016: 64).

2.3.1.2 Gamblers Fallacy

The other bias is not understanding the importance of the sample size, which leads to concluding limited evidence, or what Rabin refers to as the "gambler's fallacy effect" (1999). Investors who choose incorrect selections and make investments with the expectation of profiting end up losing them on occasion, however, investors who make informed decisions benefit significantly more from speculations. According to Andreassen and Kraus (1990: 368), when prices fluctuate, individuals tend to buy on drops and sell on ascents, which is consistent with the gambler's fallacy. Additionally, they offered proof that participants who favor chasing trends when a clear pattern emerges employ less of this type of strategy.

2.3.1.3 Representativeness

The representative heuristic is defined as the tendency to calculate the probability of an event occurring in the future based on how similar it is to the typical instance in the past (Guo et al., 2017: 184). However, this method may result in

incorrect predictions for the future. When buying stocks on the stock market, investors employ this heuristic, which encourages them to purchase previous winners. This heuristic's adherents believe that the past can forecast the future. Investors are influenced to choose investments based on the management style, current financial soundness, reputation, price-to-earnings ratio, and products the company is offering. Depending on the results of recent investments, if an investor's previous investment decisions resulted in success, they will likely make the same choices for future investments without taking into account various patterns of volatility. This is comparable to overgeneralizing based on recent experiences. When investors strive to purchase trending or profitable stocks rather than underperforming stocks, it demonstrates representative bias and overreaction on their part (Barber et al., 2009: 628).

2.3.1.4 Herding Effect

Humans have the propensity to refer to, monitor, and mimic the actions of others whether financial markets are unpredictable (Yu et al., 2018: 222). Investors do not make rational investing decisions when herding is present. They like to base their investment decisions on the beliefs and views of other investors. The herd effect was described by Akonishok et al. (1992: 314) as when investors buy or sell equities simultaneously time as other investors. Scharfstein and Stein (1990: 431) noted that the herd effect would affect the efficiency of the security market, resulting in the fluctuation of stocks' prices. Williams (2013: 639) notes that even logical and competent experts might become trapped in herding behaviors when there are attractive new investments whose result is uncertain.

The herding effect is more severe when there are market distress factors present, such as market anomalies, price bubbles, and misinformation (Mertzanis and Allam, 2018: 56). Lack of information intensifies herding behavior even more (Ben Mabrouk, 2018: 123). Some investors follow the knowledge and decision-making processes of other people while making decisions. Instead of gathering exclusive details about possible investment options, they depend on publicly available data. The concentration

of investors' attention can be inconsistent and quickly shifted by others, particularly by professionals, according to Shiller (1984: 73).

2.3.1.5 Overconfidence

According to Frank (1935: 83), who studied the problem of overconfidence in work, traders were overconfident in their skills and that overconfidence intensified with the task's importance. High trading volume, volatility, and irrational prices, according to Odean (1998b: 1832), are effects of overconfidence. Men are reportedly more overconfident than women, according to Barber and Odean (2001: 1231), and as a result, men engage in more trading than women. One of the fundamental tenets of the behavioral finance field is overconfidence. Overconfidence is a strong psychological byproduct that has been researched as one of the main causes of market anomalies (Ko and James Huang, 2007: 559).

One definition of confidence is having full trust in yourself. When an investor is working with securities and is overconfident in his or her approaches and mentality, overconfidence bias will affect the investor (Huang et al., 2014: 371). Overconfidence is a prevalent psychological bias that, according to behavioral finance, causes financial markets to be inefficient by leading to mispricing in the form of extremely high fluctuation and return variability (Ko and James Huang, 2007: 559). A psychological bias known as overconfidence leads a person to overestimate the importance of a factor and causes impaired and inadequate judgments. With those decisions, a person would never realize the proper distribution. Overconfidence bias has attracted a lot of attention and is widely applicable to rational agents' actions. (Dubra, 2004: 482). A well-known bias called overconfidence causes investors to be overconfident in their knowledge and abilities and to neglect the risk associated with their investment decisions (Prosad et al., 2018: 123).

Because they place the majority of their funds in businesses, they are familiar with or have better knowledge about, overconfident investors concentrate less on diversification (Johnson et al., 2013: 88). They overestimate the accuracy of the knowledge they possess, underrate their willingness to take risks, and overestimate

their ability to manage and control various occurrences due to their excessive confidence. According to studies, the overconfidence bias is frequently caused by the ignoring of unknown factors (Walterset et al., 2016: 143). Unexpected situations can lead to overreaction and overconfidence (Hirshleifer, 2001: 45). According to research (Graham et al, 2009), excessive overconfidence causes an extreme volume of trade and more price fluctuations in the stock markets. Investors tend to overreact because they are overconfident in their capacity to understand or analyze data (Daniela and Hirshleifer, 2002: 21). Overconfidence is a judgment error that the people exaggerate their competence, insight, perception of data or the likelihood that a given outcome will occur (Campbell et al, 2004: 63). When the evidence is confusing and the certainty is minimal, professionals exhibit higher overconfidence than regular investors, according to Griffin and Tversky (1992: 73). When they have optimistic information, institutional investors, according to Scheinkman and Xiong (2003: 1217), continue to purchase expensive equities because they feel confident selling them to others with more extreme beliefs. Due to their recent consistent growth and greater investment, most investors disregard the risk and uncertainty factors, increasing the likelihood of loss.

2.3.1.6 Overreaction

Cognitive and psychological biases against new information might cause individuals to show emotional responses about a security leading to the security being oversold or overbought. This often happens to personal characteristics such as fear or greed. This indeed is against the common framework where pricing takes place perfectly with publicly known information (Kenton, 2018: 231). This should be noted that such behavioral structure has already been pointed out in history as Issac Newton states that “What goes up must come down.” This statement however does not seem strange as the acceptance of high-performance securities tends to get reversed from one period to the other one (DeBondt and Thaler,1985: 803).

The idea behind the overreaction hypothesis asserts that stock prices are subject to optimism and pessimism as their value may change over a piece of bad or good

news. However, in the long run, they tend to obey the fundamental rules as the market suggests. The critical point to look at is right before a reversal high-performing securities might be sold-out and low-performing ones might be purchased leading to the acquisition of abnormal profit which is against EMH (Fama, 1970: 415). This has led to investigating overreaction hypothesis and developing of new theoretical and behavioral models in economics (DeBondt and Thaler, 1985).

DeBondt and Thaler (1985: 802) observed monthly return data for NYSE from 1926–1982 and concluded extreme ups and downs over this period. They constructed two portfolios namely as winner and loser in which they consisted of extremely high and low-performing securities, respectively. They showed that the winner portfolio affected the market by 19.6% while this was around 5% for the loser portfolio. Thus, they concluded that there exists a residual of 24.6% between these portfolios. They discovered that stocks that have below returns generated noticeably better returns in the subsequent time frame. The winner-loser effect is the term used in literature to describe this effect. In their essay "Does the stock market overreact?" They suggested that investors are not quite as rational as believed. Instead, they frequently exaggerate current information and disregard long-term data. Institutional investors, on the other hand, have a tendency to underreact, which implies they are typically confident in their judgment and are not prone to changing their thoughts.

Later this idea was further investigated by Brown and Harlow (1988: 12) who studied the magnitude of overreaction. Their results indicate that as the initial price extremely changes, the offsetting reaction against this change is also extreme. Additionally, as the initial price changes more rapidly, the subsequent reaction takes place more extreme. The work of Debondt and Thaler (1985: 802) was later verified by researchers such as Poterba and Summers (1988: 58) and Fama and French (1988: 271), where Fama and French (1988: 273) argued that around 25% of monthly returns can already be predicted in a course of 3-5 years. In addition to the work of Debondt and Thaler (1985: 803), some researchers argued that there exists a short-run overreaction effect (Brown and Harlow, 1988: 13; Howe, 1986: 124; Bowman and Iversan, 1998: 488)

There is a set of critiques against the Overreaction Effect as DeBondt and Thaler (1985: 803) show there exists an irrational behavior in the stock market as investors overweight new information and underweight past information. This in turn leads to excessive optimism and pessimism about good and bad news leading prices to change away from their fundamental values. This has resulted in skeptical views against the Overreaction Hypothesis leading to different explanations against this phenomenon.

A crucial factor when analyzing the Overreaction Effect is the risk incorporated between portfolio formation and the test period. Chan (1988: 131) showed that prior performance has an impact on the risk level of loser and winner firms which do not stay constant over time. His results indicate that abnormal returns do increase expected returns. Later Ball and Kothari (1989: 71) investigated a similar case concluding that change in risk level causes a negative serial correlation in returns. They showed that an increase in the level of negative abnormal returns will increase the level of leverage resulting in an increase in returns. They confirmed the impact of time-varying risk on the mean reversion returns. In another work, Jones (1993: 151) argued that the leverage effect does not influence the positive covariance. He suggested that the occurrence of overreaction is because of market movements. Moreover, the pattern in returns can be explained by rational time-varying expected returns.

Currently, it is widely accepted that overreactions cause considerable asset price deviations from their fundamental values and typically result in price corrections. The overreaction theory states that if investors overreact during a certain time, they will move in the opposite manner during the next period. The momentum effect occurs in the short run when investors overestimate an asset's inherent value. The overreaction theory is supported by the longer-term tendency of the asset price to converge to its intrinsic value. From the standpoint of an investor, early detection of an overreaction is essential to profit from trading the following counter-reaction. Overreactions are examined to evaluate market efficiency and to investigate potential profit that may be taken advantage of with the proper trading techniques.

Investors frequently overreact due to irrational bias, which causes them to give information a higher weight than it deserves (Wu, 2004: 11). At least 10% of investors overreact while making decisions, according to Russell (2000: 204). De Bondt and

Thaler (1990: 803) enquire about the role that security experts may have in the stock market's tendency to overreact. Most financial theorists would agree that securities analysts belong to a group known as "smart money" and should control overeager investors by maintaining completely rational price goals. De Bondt and Thaler discover, however, that the forecasts made by experienced security analysts exhibit the same template of overreaction as those made by unintelligent undergraduates. This finding raises more questions about the hypothesis that smart money will arbitrage noise outside of the stock market.

Cox and Peterson (1994: 264) validated overreactions for the years 1963 to 1991 and described the size effect they had found as a potential stand-in for the bid-ask bounce. Stocks have a tendency to overreact to uninformed occurrences but not after informed events, according to Larson and Madura (2003: 124), covering the years 1988 to 1995. Prior literature has also looked at the overreaction to particular events. Investigation of the overreaction to earnings announcements in the US is done by Zarowin (1989: 333). Seyhun (1990: 1696) investigated the trading practices of insiders in the NYSE, ASE, and NASDAQ equity exchanges around the time of the stock market collapse in October 1987. In the three years after the crash, extreme losers turned out to be winners thanks to insiders being large purchasers, which is evidence in favor of the overreaction hypothesis, according to the author. Jegadeesh and Titman (1995: 989) explored how stock prices in the US responded to general factors and firm-specific data. They discover robust evidence of market overreaction to firm-specific information as well as evidence of market underreaction to common stock market variables.

Using two psychological biases—overconfidence and biased self-attribution—Daniel et al. (1998: 211) offered a hypothesis of market under- and overreactions. According to their argument, an investor who has excessive confidence overestimates the accuracy of his private information signal but not the information signals that are publicly received by everyone. This overestimation of investor signals can cause asset mispricing and, as a result, deviations from intrinsic value. The authors contend that self-attribution bias could eventually lead to overreactions. Investors have a propensity to blame external factors for their losses while attributing their wins to their own skills. This bias causes "new public signals on average to be perceived as validating his

private signal." This implies that an earlier private signal may cause an additional overreaction in response to public information. The price, in general, swings even closer to the full-knowledge value on successive days as more public information emerges. This is known as a reversal effect. In light of this, the self-attribution bias may result in "short-run momentum and long-term reversals."

The short-term overreaction in the foreign exchange markets is examined by Larson and Madura (2001: 177). They conduct an empirical analysis of a sample of industrialized and developing markets to determine how dramatic one-day exchange rate changes will affect them. In industrial economies, they discover evidence of investor underreaction, while in emerging economies, they uncover signs of investor overreaction. Ma et al. (2005: 111) examined the price history of Nasdaq stocks during 1996 and 1997 and discovered convincing proof for price reversals following overreactions. According to George and Hwang (2007: 2895), the overreaction theory is primarily justified by the systemic errors made by irrational investors in reacting to new data.

Jones and Johnstone (2012: 412) discovered that two-thirds of analysts seemed to have a buy or hold rating on the stock at the time of failure after studying analyst recommendations of companies soon before filing for bankruptcy. Additionally, 73% of analysts in America gave the company a buy or hold rating, which increased the discrepancy there. This serves to further demonstrate analyst optimism and overreaction. Ni et al., (2015: 226) claim that the degree of market overreaction is positively correlated with past earnings releases, indicating the presence of a representational heuristic in investor judgments while trading stocks. In their 2017 article, Piccoli et al discover that stocks frequently overreact to both positive and negative news, however, the latter is more prominent. They studied a total of 663 events—310 positive and 353 negatives—and discovered substantial evidence that the Overreaction Hypothesis was supported statistically and economically.

Caporale and Plastun (2019: 1151) looked at the Foreign Exchange (FOREX), commodities, and US stock markets in terms of short-term overreactions. They validated overreactions in the stock market, as well as partially in the FOREX and commodity markets.

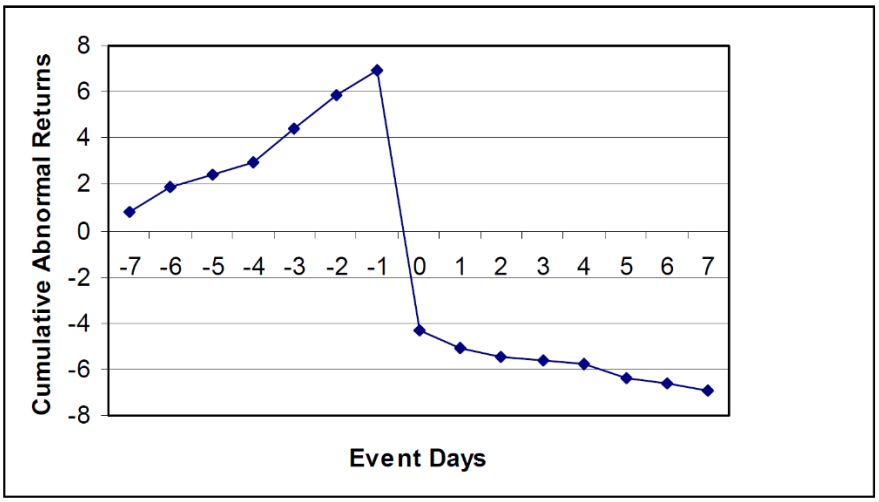
Two case studies will be given to emphasize the impact of the Overreaction Effect on various stock markets.

2.3.1.6.1 Case Study I

There are many papers examining the overreaction effect in stock markets. For instance, Borsa Istanbul (BIST) has been one of the attractive markets to invest in, which was established in 1986. Foreign investments have increased from around 2% in 1990 to 75% in 2008. In their study, Vardar and Okan (2008: 166) used daily data to analyze the trading behavior of investors considering the Turkish financial crisis in 2001. They took into consideration 190 stock prices for the period from 1999 to 2003. They divided the period into two pre and post crises periods.

To show the short-term overreaction effect, they considered the raw return of data and computed the abnormal return for each stock. After selecting winners and losers for two periods, they reached 485 winners and losers for the pre-crisis period and 701 winners and losers for the post-crisis. As Figure 2-4 shows, cumulative abnormal returns indicate a significant increase in price during just one trading day.

Figure 2-4: The Overreaction Effect seen in ISE stock data.



Their analyses show the existence of the Overreaction Effect. Moreover, stock pricing depends on good and bad information heavily dominated by the news. These results indicate that to reduce the risk during the crisis, investors become more dependent on bad news and information. They also show that an increase in initial price increases the magnitude of overreaction. They specifically claim that there is short-term evidence of Overreaction in winners. However, there is no considerable evidence of overreaction in losers.

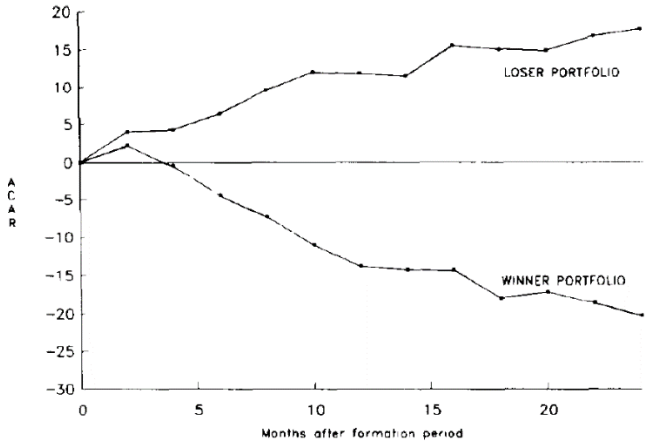
2.3.1.6.2 Case Study II

Another study dates to 1990 when there were a considerable number of companies in the Brazilian stock market in which half of these companies were actively trading. By 1989, around 57% of the market was governed by the Sao Paulo stock exchange (BOVESPA) with a market value of $B44. During this study, foreign investment was not allowed in BOVESPA.

The data used for this study included a sample of 121 stocks in BOVESPA from January 1970-1989 which accounts for 70% of trades in BOVESPA. The return rate of national treasury bills was completely risk-free. The majority of information was retrieved from BOVESPA itself. The methodology employed was similar to the previous study where monthly returns were calculated for each stock. Note that a logarithmic transformation was used in doing this. Then market-adjusted returns were calculated. Later the market-adjusted abnormal returns were calculated for each stock. For each stock, the cumulative market-adjusted abnormal return was calculated for 8 portfolios. Then cumulative average abnormal rate was calculated for all the portfolios.

In the next stage of this study, a number of statistical t-tests were implemented where the variance for the samples was assumed to be unknown. Figure 2-5 shows the performance of winner and loser portfolios from months 0 -24. As one sees, abnormal returns show a monotonic decrease.

Figure 2-5: The Overreaction Effect noticed in BOVESPA stock data.



According to the results obtained, there exists an Overreaction Effect in the stock market. This effect is mostly visible around the mid-1980s. Evidence from markets shows that the magnitude of the effect shown in this market was pronounced. Results also show the overreaction seen in this study was asymmetric where the winner portfolio showed a reversal behavior.

2.3.1.7 Other Heuristic Behaviors

Investors always attempt to focus on the bright side of decisions while neglecting the unpleasant information that demonstrates the anticipated lower return and performance of investments (Beshears, 2011: 671). This is called Escalation of Commitment.

Availability bias is another factor that means the tendency for people to base their assessments of the likelihood of an event on past experiences rather than on the actual data that has been gathered (Patrick and Charles, 2011: 114). Decisions are based on the importance of the information. Investors evaluate the information according to its significance before decision-making. This method can sometimes result in losses or lower returns. According to Tversky and Kahneman (1974: 1128), investors would assume a larger possibility of a rising trend of a stock as a result of media attention.

The human interpretation of luck and beliefs might have an impact on investment decisions. Some people have an extremely low level of rationale because they are superstitious and believe that luck will determine how things turn out.

According to statistics, the majority of investors prefer to purchase stocks from domestically based businesses. Investors have grown up with the names of these companies, making these equities seem more reliable. Additionally, they receive more coverage in the regional media. Because of investment restrictions, transaction costs, and other uncertainties, investors prefer investing in domestic securities over overseas securities. Thus, home bias has an impact on investor judgment. Wang et al. (2011: 213) examined how someone's familiarity with a financial product influences their perception of its riskiness. No matter how risky an investment may be on the surface, investors have been found to attach much less risk to assets they are aware of. They included the bias to believe that domestic assets were safer than overseas ones.

Institutional investors, in particular, are more likely to credit positive results to their own abilities and negative results to outside factors (Hirshleifer, 2001: 56). A further claim made by Hirshleifer (2001: 74) is that overconfidence and self-attribution are dynamic and static counterparts, with overconfidence resulting from self-attribution rather than converging to genuine self-evaluation.

Confirmation bias describes the phenomenon of searching for only the information needed to confirm one's own beliefs or to interpret the information in a manner consistent with one's own perspective. Investors look for evidence to support their hypotheses. They avoid opposing views and news coverage, reading only articles that support the view they hold.

According to the attention bias, when investors are searching for an appropriate investment instrument, they will remember items like products, companies, and issuers that are more regularly featured in the media more rapidly. Unconsciously, unreliable, or difficult-to-access information is ignored.

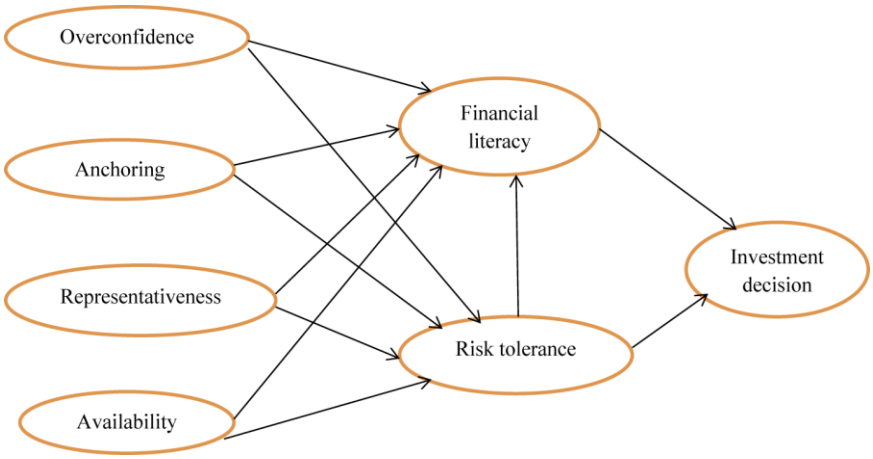
Often people conclude an event after an event has already happened, anticipate the outcomes, and make minor revisions to their plans. I knew this would happen the

entire time, which proves that everything can be explained after the fact. The problem with hindsight is that it prevents us from learning from our errors.

Investors' tendency to avoid taking losses when they expect to obtain gains is known as the disposition effect (Pelster and Hofmann, 2018: 86). According to Odean (1999: 115), the disposition effect is calculated as the distinction between the proportion of realized profits and losses (Odean et al., 2010: 1921). It has been researched how disposition affects equity premium. A study found that the presence of the investor disposition effect causes investors to resist greater risk premiums when investing in equities (Roger, 2009: 321). The study discovered that international and institutional investors are less likely than individual investors to experience the disposition effect. The willingness of investors to keep losses in investments for a longer duration of time and sell winners in investments too soon has been noted by researchers as the disposition effect. The disposition effect negatively affects a person's investment since failing investments typically continue to underperform, while winning investments typically continue to thrive (Aspara and Hoffmann, 2015: 522).

Figure 2-6 shows how some heuristic behaviors and investment decisions interact (Kasoga, 2021: 455)

Figure 2-6: Heuristic biases and investment decisions.



Source: Retrieved from Kasoga (2021: 455)

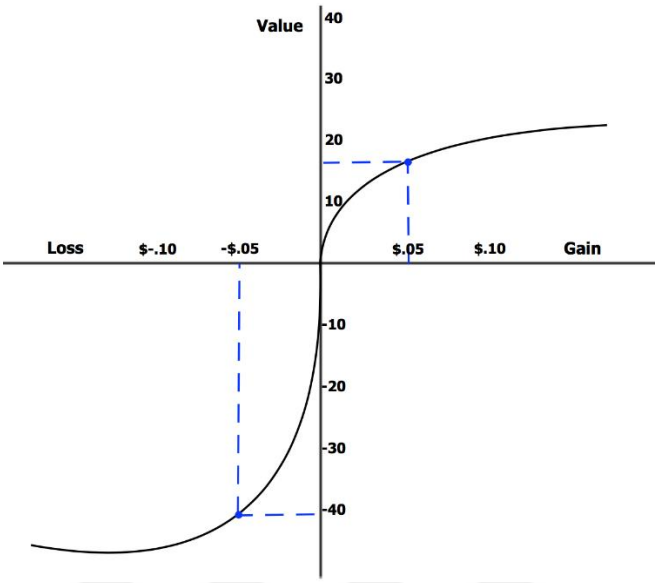
2.3.2 Prospect Theory

A behavioral model known as "prospect theory" demonstrates how people make choices between options that incorporate risk and uncertainty. People are much more likely to take risks to avoid losses because they dislike losses more than they like similar profits.

2.3.2.1 Loss Aversion

The majority of investors fear losses more than they relish earnings. If these investors monitor their stock performance frequently, they typically discover that they have lost money and resell everything. Behavioral and cognitive strategies result in risk-averse behavior in the case of profit and risk-seeking behavior in the case of potential losses. Loss aversion is the term for this phenomenon. According to Hirshleifer (2001: 114), loss aversion is the tendency of people to avoid risks when compared to a reference point in the utility function. The purchase price and selling price are typically the only reference points utilized in behavioral finance when examining a bias. Loss aversion might cause excessive stock price volatility, according to research by Barberis and Huang from 2001. The momentum effect can also be addressed by loss aversion, according to Grinblatt and Han (2005: 324). Investment losses are generally felt with considerably greater intensity than gains (Li, 2012: 417). Despite EMH's contention that people assess wins and losses equally, the truth is that people hate losing money. The value function shows that different outcomes will have distinct relative values for investors. Figure 2-7 shows an s-shape and asymmetrical value function to represent loss aversion (Li, 2012: 418).

Figure 2-7: Loss aversion depicted in an asymmetrical shape.



Source: Retrieved from https://en.wikipedia.org/wiki/Loss_aversion.

2.3.2.2 Other Factors of Prospect Theory

The mental accounting technique of psychology, which consists of three parts, influences the pattern of investing actions that fulfill this pattern. One element describes the evaluation of decision-making processes and how returns are calculated. A second element guides actions toward specific accounts. The third element refers to the availability of options and their frequency. Losses suffered are frequently seen as distinct from paper losses. This implies that consumers sell their portfolio's holdings of stocks both too soon—when they make a profit—and too late—when they lose money (Li, 2012: 417).

There are several investment options, but most investors choose the one that speaks or listens to in social circumstances the most. Decisions are majorly dependent on how statistics represent the facts. For example, we do not equate the phrases "Four out of ten are winners" with "Six out of ten are losers." The majority of individuals are unaware that the sentence is identical.

We refer to it as bad luck if we buy in a blue-chip stock (a giant company with a stellar reputation), and it fails to perform as anticipated. However, we often regret investing in a niche product that does not perform well more than we regret the failure of the blue-chip stock. This is so that our decision to purchase it does not appear so terrible because many other people have committed the same error. Investors who have a regret aversion never want to experience the frustration of regret due to poor investing choices. Due to investor purchases of underperforming equities, many stocks are never put up for sale. By demonstrating investment losses, low stock income is then taxed at a lower rate. Always seeking to avoid losses, decision-makers look for safe investment opportunities (Li, 2012: 402).

Decisions are influenced by psychological biases as well as personality traits that play a role in the decision process. Research by Paul Slovic (1972, 713), for example, asserted that behavioral biases and investor type are significantly related. Applying a market experiment, Witteloostuijn and Muehlfeld (2008: 821) discover that various personality types influence many aspects of trading behavior and, consequently, trading performance.

In order to determine whether there is any observable relationship between personality and the approach that someone invests their money, Bucciol and Zarri (2015: 118) examined vast amounts of information on the characteristics of individuals and the consequent allocation of capital investments. This essay demonstrates how one views their life, and the outside world can definitely affect their financial decisions.

Emotions have little weight over these investors. However, they lack the financial expertise needed to appropriately evaluate risks and opportunities. Realistic investors are advised to seek professional investment advice. They can gain a better financial understanding and make better-investing selections as a result.

Reliability, self-control, and the ability to manage one's own motivation are traits of the conscientious mentality, along with making sensible decisions. A conscientious individual has the capacity to anticipate risks, which leads to variations in decisions to modify risk in order to maximize profit.

Extrovert investors consider external factors, such as knowledge about opportunities from outside sources, while making investing decisions. Extroverts focus on outward judgments and evaluations instead of using their own personal decision-making skills. More extroverted people tend to make decisions more quickly because they prioritize the moment over adhering to rules and regulations. The traits of extroverts that can affect investments are a lack of internal control, limited intellectual capacity, and poor effort (Bucciol and Zarri, 2015: 118).

Exploring investors have a strong understanding of the financial market yet make emotional choices. They have a thorough understanding of the market's opportunities and risks. Despite occasionally being captivated by cutting-edge financial solutions, they always keep the risks in sight. Even though they have a wealth of financial knowledge, investors occasionally change their predetermined investing strategy due to emotional factors. Because of this, their investments must be routinely examined to ensure that they adhere to the investment strategy.

According to research on cognitive psychology, conservatism is a bias that can appear when people process information in a way that makes them more likely to concentrate on their prior knowledge or information and less on the latest information. On the stock market, conservatism may cause traders to take their time adjusting to fresh information. Recent research demonstrates that announcements on earnings, dividends, stock splits, and other events typically generate underreaction from investors.

Strategic investors understand the financial markets well, which allows them to evaluate the dangers and opportunities they are now confronting. Additionally, they are unbiased decision-makers who are not affected by emotions. They are unable to lose track of their investment objectives thanks to their strategic strategy.

Investors that exhibit neuroticism take action to fulfill their own personal objectives. They always make choices that favor them since they have a self-centered and egotistical personality. They do not require social values because they make their decisions in a scenario of self-assessment and self-interest.

This should be noted that investors with intuition make emotional choices. Without the proper investment plan, there is a chance that they will be overly affected by recent market trends and forget their investing objectives. To enable emotional investors to stick to a predetermined investment strategy, a discretionary mandate is advised. According to surveys, the investing strategy accounts for around 80% of investment gains.

Everybody with an agreeable personality will weigh the opinions of others while making decisions because of emotional ties. His genuineness and truthfulness with others demonstrate that meeting others' needs is his top focus. When deciding whether to invest money in a partnership business, these agreeableness traits are most important.

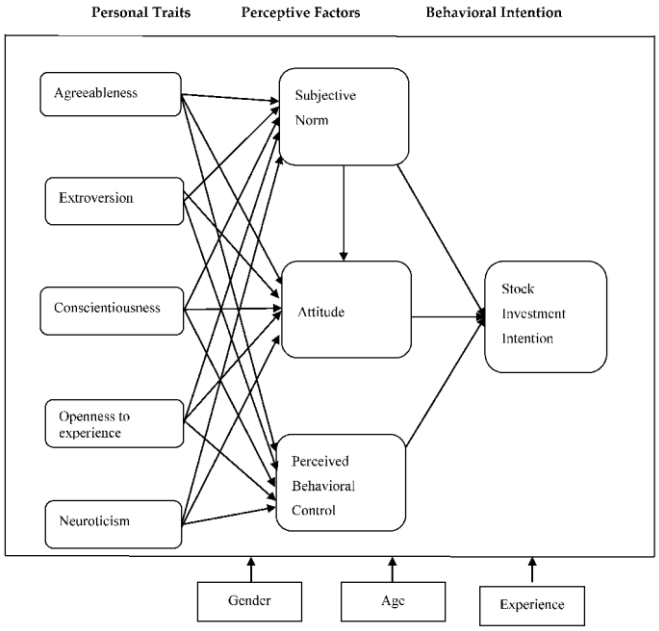
Decision-making is influenced by emotions, ecological elements including the environment, the body's biorhythms, and societal issues. Investors occasionally have sentiments about a project, regardless of whether it is dangerous or offers a high return. For this reason, behavioral finance experts have suggested that feelings have a connection to risk phenomena. If there is a risk of unfavorable results, investor loss aversion emotions must be used as a peacemaker.

Since institutional investors are more susceptible to these biases, it is impossible to reduce or completely eradicate them through studies and experience. According to Hirshleifer (2014: 113), additional study is required to better understand the behaviors and motivations that influence decision-making. Hirshleifer contends that behavioral finance must transform into social finance. Social finance, according to Hirshleifer, is the study of how "social norms, moral attitudes, religions, and ideologies affect financial behaviors." Even if we suppose that investors across the globe are concerned with the return/risk trade-off, researchers think that culture can have a significant impact on investors' choice of investment strategy, the time horizon for making investments, and risk aversion. Which psychological traps we are more prone to fall into depends in part on our society. Due to differences in culture, values, financial market infrastructure, financial literacy, and educational attainment, it is problematic to extrapolate the results of studies done in industrialized nations to emerging nations. Thanks to significant technical advancements, a new approach called neurofinance has

recently been used in economics and is currently also being applied to financial sciences. We can identify which traps are biologically based and consequently more challenging to escape thanks to neurofinance.

Figure 2-8 shows how various personal characteristics lead to the intention for stock investment.

Figure 2-8: Interrelation of personality characteristics and stock investment.



Source: Retrieved from Hirshleifer (2014: 113).

3 CHAPTER III: LITERATURE REVIEW

This section provides a deep literature review on concepts such as Efficient Market Hypothesis (EMH), Behavioral Finance (BF) including behavioral biases specially Overreaction Effect (OE) in cryptocurrency markets. The main objective of this chapter is to get familiarized with the background behind these concepts and get in line with the most recent research in which the OE has been investigated both theoretically and in an applied sense.

3.1 LITERATURE ON EMH FOR CRYPTOCURRENCIES

The rapid development of Bitcoin and other digital currencies since its introduction by Nakamoto (2008: 1) has led to an uprising of interest coming from governments, academics, investors, traders, and portfolio managers. Total market capitalization for crypto markets exceeded $T 1 by June 2023. This brings the idea that maybe investors treat cryptocurrencies as assets rather than currencies. An increasing amount of academic research has been conducted to examine the volatility and returns traits of Bitcoin, the most well-known cryptocurrency. Whether or not such markets are compatible with the Efficient Markets Hypothesis (EMH) is one of the major features of digital currencies that has drawn increasing curiosity.

The key concept of the realm of finance, the Efficient Market Hypothesis, was developed by Fama (1970: 384). When "prices reflect full information" in a market, according to Fama, "informational efficiency" is present. These are the primary categories of informational efficiency that are most frequently used. First, the prices of assets reflect all the information that has been concealed in prior prices for these assets. Second, semi-strong efficiency denotes that current prices represent all available publicly accessible information. Third, prices now reflect any and all data, private or public, as is represented by strong-form efficiency. The weak-form EMH is the most often used of the three forms of EMH. It illustrates that it is impossible for

investors to use previous prices of assets to forecast the potential future worth of these assets.

Numerous academic studies have examined the concept of long-range dependence and its compatibility with the Efficient Market Hypothesis. Various tests have been conducted to assess the validity of weak-form efficiency in the Bitcoin market. The majority of empirical research on Bitcoin suggests inefficiency, indicating the presence of profitable trading possibilities. However, it is important to note that the ability to outperform the market through Bitcoin investments diminishes as the Bitcoin market becomes more mature.

The early research undertaken by Urquhart (2016: 81) is noteworthy. Using daily data from August 1, 2010, to July 31, 2016, Urquhart (2016: 81) explicitly examined the informational efficiency of Bitcoin. The two nine-year subperiods that were the subject of the study were separated by the end of July 2013. The variance ratio test of Lo and Mackinlay, the wild-bootstrapped test of Kim, the Ljung and Box test, the BDS test of Brock et al, the Hurst exponent for testing long memory, the runs test, and the Bartels test were some of the tests that the author used. The Hurst exponent stated that the outcomes of these tests rejected randomness and pointed to the existence of considerable anti-persistence. Therefore, despite a trend toward a legitimate Efficient Market Hypothesis (EMH) from August 2013, the results lead to the conclusion that the Bitcoin market is not efficient.

Data from August 1, 2010, to July 31, 2016, were used in research by Nadarajah and Chu (2017: 6) to examine the Bitcoin market efficiency. By utilizing eight tests to investigate the Efficient Market Hypothesis (EMH), they built on Urquhart's (2016) study. The Bartels' test, the wild-bootstrapped automatic variance ratio test, the Ljung-Box test, and the runs test were some of the tests that were used. The bulk of them convey proof of the returns' independence. Thus, the Bitcoin market failed to observe any unanticipated profits.

Bariviera (2017: 4) used daily data from August 18, 2011, through February 15, 2017, to perform research on Bitcoin returns and volatility. Long-range dependency was investigated using the Hurst exponent, which was derived using Detrended Fluctuation Analysis (DFA) and overlapping sliding windows. The results

showed that Bitcoin's returns showed durability from 2011 to 2014, but that there was a tendency towards efficiency after that year. On the other hand, the research claimed that the volatility of Bitcoin kept going during the investigation. Additionally, the study discovered that long-range memory was not significantly impacted by various time frames. Furthermore, there was evidence that long-term dependency was unaffected by market liquidity.

In a research, Kurihara and Fukushima (2017: 57) investigated the existence of weekly price anomalies and the efficiency of the Bitcoin market. They used robust least squares (RLS) and standard ordinary least squares (OLS) approaches to analyze data collected between July 17, 2010, and December 29, 2016. According to the findings of their investigation, the Bitcoin market did not demonstrate weak-form efficiency. However, it was noted that the Bitcoin market's level of efficiency increased over time.

Alvarez-Ramirez et al. (2018: 949) used detrended fluctuation analysis (DFA) with rolling windows to detect long-term correlations in a study of Bitcoin returns from June 2013 to June 2017. The results of the study showed that the Hurst component displayed cycles, showing that Bitcoin went through phases of efficiency and inefficiency. Furthermore, depending on whether price trends were rising or falling, unbalanced relationships were seen. Due to the anti-persistence brought on by this imbalance, Bitcoin was ultimately inefficient.

Tiwari et al. (2018: 107) studied Bitcoin using daily data from July 18, 2010, to June 16, 2017. They used a variety of tests to take a closer look at Bitcoin's long-range dependencies and informational efficiency. These tests implemented the Detrended Fluctuation Analysis (DFA), Geweke-Porter-Hudak (GPH) methodologies, maximum-likelihood estimator (MLE), Centered Moving Average-squared absolute fluctuation (CMA-1), Periodogram Least Absolute Deviation (Periodogram-LAD), Centered Moving Average-mean absolute fluctuation (CMA-2), Periodogram-Least Squares (Periodogram-LS, and. The aggregate data revealed that the Bitcoin market is efficient. The subperiods of April to August 2013 and August to November 2016 both have instances of inefficiency, though.

Cheah et al. (2018: 19) carried out research on the cross-national interconnectedness of Bitcoin markets. Focusing on markets in Europe, the USA, Australia, Canada, and the United Kingdom, they used daily closing Bitcoin prices from November 27, 2011, to March 17, 2017. The researchers utilized a fractionally cointegrated VAR (FCVAR) specification and considered cross-market Bitcoin prices as long-memory processes in their research. The findings of their investigation showed that these markets exhibited informational inefficiency, indicating that information was not fully and synchronously absorbed into pricing.

A research on the efficiency of Bitcoin before and after the introduction of Bitcoin futures was undertaken by Köchling et al. (2018: 368). Data from the pre-launch period, which ran from August 10 to December 10, 2017, and the post-launch period, which ran from December 10 to April 10, 2018, were both examined. To determine how the introduction of Bitcoin futures will affect Bitcoin's efficiency, the researchers ran several efficiency tests. Nine experiments were run, and seven of them showed inefficiency prior to the launch of Bitcoin futures. But with the introduction of Bitcoin futures, no inefficiency was found, demonstrating the existence of weak-form efficiency.

Kristoufek (2018: 258) investigated the efficiency of two Bitcoin markets: one with the US currency and one with the Chinese yuan. For the US dollar market, the research's data began on July 18, 2010, and for the Chinese yuan market, it began on February 1, 2014. Both markets' data were used for the study, which lasted through July 2017. To evaluate efficiency, the researcher utilized the Efficiency Index (EI), which was created by Kristoufek and Vosvrda (2013: 189). The Hurst exponent, fractal dimension, and entropy were also used as metrics. The research's conclusions showed that the US dollar market operated efficiently from mid-2011 to mid-2012 and from March to November 2014. The US and Chinese Bitcoin markets, however, were largely inefficient during the course of the seven-year period under consideration, according to the overall empirical findings. Efficiency was only seen when Bitcoin prices were at their highest levels.

In addition, Phillip et al. (2018: 7) carried out a research utilizing daily data on Bitcoin, Ethereum, Ripple, NEM, and Dash from several trading platforms through

July 31, 2017. The researchers used the GLM-SV-LGV-HT model to calculate the heavy tails (HT), the generalized long memory (GLM), leverage (LVG), and the stochastic volatility (SV), and the results showed that as the markets developed, these highly financed cryptocurrencies displayed comparable long-memory traits. The study offered proof that the markets for digital currencies, such as Bitcoin and others, were inefficient. Importantly, the traits of long memory, heavy-tailedness, stochastic volatility, and leverage could be seen in all the tested cryptocurrencies.

Using daily data from a number of cryptocurrencies, including Bitcoin, Ethereum, Ripple, Litecoin, Stellar, Dash, Monero, and Nem, Zhang et al. (2018: 659) performed an analysis. Data were collected between April 28, 2013, and April 30, 2018. The researchers used a number of statistical tests and analytic methods, including skewness, GARCH and GJR specifications, kurtosis, cross-correlation analysis using the detrended moving average, Jarque-Bera tests, and autocorrelations. The study found that the Bitcoin market was becoming more efficient as the exponent's value approached 0.5 by employing the Hurst exponent with rolling windows. The study also looked at long-range dependency and found that these cryptocurrencies showed signs of power-law association.

In their analysis, Brauneis and Mestel (2018: 59) used daily data on 73 digital currencies, including prices, dollar volume, and market capitalization. The information covers the time frame of August 31, 2015, to November 30, 2017. The researchers wanted to investigate how efficient these digital currencies are. The Ljung and Box test for autocorrelation, the Kim wild-bootstrapped VR test, the runs test, and the variance ratio test were only a few of the statistical tests they used to evaluate efficiency. According to the study's findings, Bitcoin was the most effective cryptocurrency considered. It is noteworthy that increased inefficiency in a digital currency was correlated with higher liquidity levels. This suggests that the possibility of generating unusual gains was larger when there was more liquidity.

In a research published in 2018, Charfeddine and Maouchi (2018: 424), used the daily closing values of Litecoin, Ethereum, Ripple, and Bitcoin. The information covers the time frames from each cryptocurrency's introduction through February 2018. The goal of the study was to determine whether long-range dependence (LRD)

existed in these digital currencies' returns and volatility. The study's empirical results showed that three of the four digital currencies under investigation have inefficient marketplaces. It's interesting to note that the study only found Ethereum to exhibit market efficiency.

The four cryptocurrencies with the biggest market capitalization—Bitcoin, Litecoin, Ripple, and Dash—were studied by Caporale et al. (2018: 141) using daily data. The data was as extensive as it could be up to 2017. To examine the properties of various cryptocurrencies, the researchers used fractional integration and R/S Hurst analysis approaches. The study's findings showed that the persistence of cryptocurrencies did not remain constant over time, causing considerable changes. In the instance of Litecoin, this tendency was quite obvious. The results showed that the efficiency of cryptocurrencies improved with time and validated Lo's (2004: 14) Adaptive Market Hypothesis. In the beginning, Litecoin was more inefficient than the other cryptocurrencies. Bitcoin, Litecoin, and Dash appeared to be relatively more efficient than Ripple, according to the values of the Hurst exponent. Despite signs of improvement, as seen by the declining Hurst exponent, the study's overall conclusion was that the Bitcoin market was still inefficient. Consequently, there were still chances to engage in profitable cryptocurrency trading.

Research by Chaim and Laurini (2019: 33) used information from nine significant cryptocurrencies: Bitcoin, Ethereum, Ripple, Litecoin, Stellar, Dash, Monero, Nem, and Verge. The information covers the time frame from 16 August 2015 to 31 October 2018. In order to take into account frequent jumps in the mean and volatility of returns, the researchers used a multivariate non-linear stochastic volatility model that was developed by Laurini et al. (2016: 88). The model used a combined Markov Chain Monte Carlo (MCMC) method in addition to a Bayesian mechanism. The study's results showed that there were considerable transitory mean jumps, which have increased in size and frequency since early 2017. The researchers used simulations to show that stationary models with jump components were effective in capturing the properties of long-memory dependency.

Kaiser (2018: 233) carried out research utilizing daily data for 10 cryptocurrencies: Bitcoin, BitcoinCash, Cardano, Dash, Ethereum, IOTA, Litecoin,

NEO, Ripple, and Monero. The goal of the study was to look at seasonal trends in these cryptocurrencies' returns, volatility, trading volume, and spread estimator. The study focused on five impacts, including the Monday effect, weekend effect, January effect, turn-of-month effect, and Halloween effect. Overall, according to the study's findings, the Efficient Market Hypothesis (EMH) could not be disproved. This means that, in terms of the analyzed factors, there are no discernible seasonality trends in the market for these cryptocurrencies.

A research was carried out by Köchling et al. (2019: 39) utilizing information from around 75 cryptocurrencies between August 31, 2015, and August 31, 2018. The researchers were particularly interested in cryptocurrencies with a market value of at least $1 million. The goal of the study was to evaluate the three-delay metrics put out by Hou and Moskowitz (2005: 991) to determine how long digital currency markets take to incorporate pricing information. According to the study's findings, there were noticeably fewer price delays in the cryptocurrency marketplaces throughout the period under investigation. This shows that the time required for digital currency exchanges to update with fresh pricing information has gotten shorter over time. The findings imply that bitcoin markets have improved in efficiency over time.

Demand and supply are only partially able to account for bitcoin prices that are experimentally seen in markets, according to Athey, Parashkevov, Sarukkai, and Xia's (2016: 5) effort to explain bitcoin pricing by bitcoin usage as a payment method. Furthermore, they discover that investors and occasional users own the bulk of Bitcoin. When considered with other data, it is doubtful that the prices of cryptocurrencies accurately reflect their worth.

Investors that believe they can sell an inflated asset for a profit at a higher price are said to be creating rational bubbles. The formation of irrational bubbles, in contrast, occurs when investors are motivated by psychological considerations unrelated to the asset's intrinsic value (Cheah and Fry, 2015: 35). According to Cretarola and Figà-Talamanca (2020: 6), the Bitcoin and Ethereum markets are prone to developing bubbles. As a result, indicators including trade volume, EPU, volatility, and the VIX show a stronger capacity for predicting crypto bubbles (Enoksen et al., 2020: 139). In

contrast to the EPU, the VIX has a negative correlation with the development of bubbles (Enoksen et al., 2020: 139).

According to Cretarola and Figà-Talamanca (2020: 6), models have been created to distinguish between bubble and non-bubble regimes in the cryptocurrency market. Price explosions can, however, take place even in the absence of bubbles (Fry, 2018: 228). The cryptocurrency industry has experienced many phases of explosive growth. The explosiveness of one cryptocurrency typically depends on the explosiveness of other currencies. Regardless of the market cap of cryptocurrencies, this co-explosivity exists. Compared to other cryptocurrencies, Bitcoin is more explosive (Bouri et al., 2019: 180). Additionally, even while cryptocurrency values are explosive, it can be difficult to ascertain the intrinsic value of cryptocurrencies; for this reason, the phrase "crypto bubbles" should only be used cautiously (Gronwald, 2021: 4).

The work of Noda, A. (2021: 438) shows that the efficiency of crypto markets changes with time. However, this efficiency varies across various currencies. He also showed that the market evolves with high liquidity. Thus, this supports the idea of the adaptive market hypothesis (AMH). This poses the question of whether there are other factors affecting the adaptive efficiency or maybe the inefficiency of cryptocurrency markets.

The fact that an extensive number of studies have provided data pointing to the existence of inefficiency in cryptocurrency markets deserves special attention. This means that there is still potential in the cryptocurrency market for investors and speculators to gain abnormal returns. Thanks to this potential, this market is appealing to many traders.

3.2 LITERATURE ON BEHAVIORAL BIASES ON CRYPTOCURRENCIES OTHER THAN OVERREACTION

The cryptocurrency market is a new market that makes it possible to analyze how the behavior of its participants influences asset values due to its speculative and difficult-to-value character. The bulk of Bitcoin market participants are speculators;

thus, the behavioral impact may be greater than in traditional markets. The general degree of investor complexity in cryptocurrency markets is substantially lower, and until recently, there were not many institutional investors (Keidan and Kelly, 2017). Despite this, cryptocurrency markets do have certain positive characteristics. Therefore, mispricing may be quite serious.

Gupta et al. (2020: 1451) assert that social factors have a significant effect on the main motivations for investing in cryptocurrencies. Numerous additional elements, in addition to social influence, affect investors' decisions to participate in the cryptocurrency market. These include a high degree of knowledge about finance, sufficient funding, high-performance standards, and an impression of pragmatism.

In contrast to traditional financial markets, where investors often consider volatility as an undesirable characteristic, investors assume substantial fluctuation in the cryptocurrency market as an opportunity to achieve more gains (Nadler and Guo, 2020: 2).

Investors in cryptocurrencies have a propensity to use behavioral trading methods, focusing on short-lived trends and making trades at hourly and daily time frames, especially in trades with significant sentiment and volume. This trend demonstrates that the bitcoin market does indeed have noisy trading (Karaa et al., 2021: 12).

Investors prefer cryptocurrencies that demonstrate large payoffs by imposing the concept of lottery-like desire in the cryptocurrency market (Grobys and Junttila, 2021: 11) and not being worried about the possibility of crashes as stock investors are (Jia et al., 2021: 6). This result suggests that cryptocurrency investors are motivated by a desire for risk (Pelster et al., 2019: 100).

Investors that have little success in the cryptocurrency market have a gambling mindset by expanding their adherence to upcoming trades through new deposits, even after experiencing losses. Unfortunately, this practice frequently results in their losing all their money in the end. In contrast, investors often don't put more money into their accounts or take money out when they have positive results. They would much rather retain their money in the cryptocurrency market (Gemayel and Preda, 2021: 6).

According to studies on the sociodemographic traits of Australian and Chinese cryptocurrency investors, Australian women are unlikely to make further investments in cryptocurrencies (Xi et al., 2020: 20). Higher-earning Australians who have previously made cryptocurrency investments are more likely to choose Initial Coin Offerings (ICO) investments that provide a long-term strategic plan, a clearly defined whitepaper, and an intuitive user interface. Chinese cryptocurrency investors, on the other hand, tend to be between the ages of 18 and 30, appreciate ICO investments, although they normally give less consideration to the whitepaper and long-term strategic strategy. In contrast, Chinese investors might have engaged in a more short-term strategy, whereas Australian investors often have a long-term outlook on investments (Xi et al., 2020: 20).

Investor sentiment has a major impact on the cryptocurrency market (Anamika et al., 2021: 211). The magnitude of this effect, however, varies according to macroeconomic and microeconomic sentiments. According to research by (Burggraf et al., 2020: 250), macroeconomic sentiment has a less noticeable impact than microeconomic sentiment, which reflects daily issues like job searching and unemployment. In addition, in the Bitcoin market, when investor emotions are negative, returns are lower, and when sentiment is positive, investors are more likely to take on risky activity.

Investors frequently switch their attention to the cryptocurrency market during times of anxiety and pessimism in the equities markets, which raises the price of cryptocurrencies (Gaies et al., 2021: 6). This finding shows that, in uncertain times, investors are disproportionately lured to cryptocurrencies (Anamika et al., 2021: 211). Additionally, when the price of bitcoin rises, both optimistic and pessimistic Bitcoin investors boost their trading volume in the short term. Investors who are optimistic continue to trade regularly whereas pessimistic investors reduce their trading volume (to prepare for potential losses) when the price of bitcoin declines. Optimistic investors will reduce their trading volume in the long run if the price of bitcoin keeps dropping (Gaies et al., 2021: 6).

The bitcoin return is shaped by variance in optimism in such a way that the spread of returns lowers when good news is announced (Caferra, 2020: 3). Because

expectations and prices rise when investors are optimistic, it becomes clear that investors' attitude affects the price of cryptocurrencies, and that the fluctuation of cryptocurrencies largely relies on investors' humor and behavior (Caferra, 2020: 4).

The cryptocurrency market is significantly impacted by public sentiment as well (Ngo and Nguyen, 2022: 1012). It is true that not all forms of social media have the same effect; for instance, tweets have less of an impact on Bitcoin's value than do postings on online forums; but it does appear that posts that are bullish are associated with higher Bitcoin prices in the future (Mai et al., 2018: 63). Additionally, there is evidence that the number of tweets on Twitter can anticipate the price returns of cryptocurrencies (Kraaijeveld and De Smedt, 2020: 11), and that the number of searches on Google can forecast the volatility of cryptocurrencies (Bleher and Dimpfl, 2019: 158). High-frequency predictions of Bitcoin price dynamics may be obtained through Chinese Baidu online searches and Baidu-Google inquiries (Süssmuth, 2021: 444).

According to Flori (2019: 347), news and media coverage appear to affect Bitcoin demand, suggesting that investors' opinions might aid them in understanding how cryptocurrencies behave. For instance, the intraday price patterns shift in the direction of sentiment following the announcement of expert news, with little market overreaction.

Positive news does not have as much of an impact on cryptocurrency investors as bad news does (de Gama Silva et al., 2019: 2836). For instance, bitcoin investors respond adversely because they view the potential implementation of regulations in the cryptocurrency market as bad news. If we take into account cryptocurrencies with more information asymmetry risk and those that are less liquid, investors respond less unfavorably (Chokor and Alfieri, 2021: 172). The news that China was banning ICOs caused huge and abnormally negative returns in the cryptocurrency market, but it also temporarily reduced liquidity levels (Zhang and Gregoriou, 2020: 1698). In contrast, the Federal Open Market Committee's (FOMC) announcements have little to no impact on Bitcoin prices (Pyo and Lee, 2020: 4), whereas macroeconomic announcements about the consumer price index (CPI) and producer price index (PPI) appear to have negligible impacts on Bitcoin prices. Additionally, it is discovered that

investors have a significant confirmation bias against news about authorities, suggesting that they have little faith in governments or central banks. As a result, comprehensible news about authorities encourages more aggressive trading behavior (Zhang et al., 2019: 1452). However, it is always possible to influence investor behavior by leveraging media (new and social networks). Pump-and-dump schemes and other cryptocurrency market manipulations use social media platforms to alert investors to buy bitcoin at artificially inflated prices so they may profit from the increase in value.

According to several studies (Rubbaniy et al., 2021: 3), (Kallinterakis and Wang 2019: 242), (Bouri et al., 2019: 218), (King and Koutmos, 2021: 90), (Raimundo Jnior et al., 2020: 49) the cryptocurrency market has been significantly dependent to media and as a result, investors display herding behavior. Murray Leclair (2018: 11) examined 12 cryptocurrencies and discovered empirical proof of herding behavior. Unlike traditional assets, cryptocurrencies exhibit sentiment trading (Kallinterakis and Wang, 2019: 242); (Stavroyiannis and Babalos, 2019: 62). They also lack the fundamentals. This is demonstrated by the fact that irrational investors dominate the cryptocurrency market and rely on their trading choices on market sentiment, which is exacerbated by the absence of an intrinsic value (Ballis and Drakos, 2020: 4), (Kaiser and Stöckl, 2020: 4). Investment decisions made for initial coin offerings (ICOs) also exhibit herding behavior and information cascades (Thies et al., 2021: 1699).

Certain conditions make herding behavior more prevalent while others appear to make it less so. In this regard, Bouri et al. (2019: 218) discovered that herding behavior increases as the level of uncertainty rises. Also, lower market regulation increases herding behavior and the proportion of irrational investors in the cryptocurrency market (Xiong et al., 2020: 1148).

In addition to the CSAD method, Coskun et al. (2020: 7) investigated the effect of economic policy uncertainty on herding behavior. The results for the whole sample, which included daily data from the 14 most well-known cryptocurrencies, indicate anti-herding behavior. Also, there was no discernible asymmetry behavior throughout the "up and down" market stages.

When the market is under stress or during moments of extreme volatility, herding behavior is more noticeable (Kumar, 2021: 306). This feature is especially important when there is a high number of transactions and a high price of the cryptocurrency (Manahov, 2021: 344), (Kallinterakis and Wang, 2019: 242), (Stavroyiannis and Babalos, 2019: 62). Smaller coins further increase the herding behavior magnitude during these times. Additionally, it appears that the rise in the dollar index and S&P 500 index has increased the degree of herding in the cryptocurrency market (Youssef, 2020: 237). In addition, investors in cryptocurrencies commonly exhibit the herding tendency during uncertain times, such as the COVID-19 pandemic (Rubbaniy et al., 2021: 3), (Bouri et al., 2019: 218). Mandaci and Cagli (2022: 6) uncover considerable herding behavior during the COVID-19 epidemic using a unique Granger causality technique with a Fourier approximation.

Contrary to these findings, data also suggests that in low-volatility regimes, investors follow other investors rather than relying on their knowledge. In contrast, investors who are overconfident under uncertainty exhibit anti-herding behavior by overestimating their capacity for financial decision-making, leading them to ignore crucial market signals (Coskun et al., 2020: 7), revealing a herding asymmetry between bullish and bearish regimes (Rubbaniy et al., 2021: 3).

To find out the presence of the disposition effect in Bitcoin, Schatzmann and Haslhofer (2020: 12) did a research. Their findings demonstrate that investors are undoubtedly susceptible to the disposition effect, with a tendency to exit winning positions too quickly and hang onto losing ones for an excessively long time. The majority of the used technical indicators have indicated that, as mentioned in their study, this influence has been quite visibly present during the volatile year of 2017 onward.

Using daily data from August 7, 2015, to December 31, 2019, Naeem et al. (2020: 1533) investigate the forecasting power of Twitter Happiness Sentiment for six significant cryptocurrencies including Bitcoin (BTC), Ethereum (ETH), Ripple (XRP), Litecoin (LTC), Monero (XMR), and Dash (DASH). Findings suggest that, with the exception of Dash, five cryptocurrencies are significantly predicted by sentiments of

happiness. Additionally, whether the market is bullish, neutral, or bearish affects whether happiness sentiment is a reliable predictor of cryptocurrency prices.

Li et al. (2020: 1143) analyze the size effect on the cryptocurrency market using a sample of more than 1,800 coins. The Efficient Market Hypothesis is put to the test by the authors of this study, who show that cryptocurrencies with low market values typically perform higher in the future.

According to Decourt et al. (2017: 10), Mondays had larger Bitcoin returns than other days. However, they came to the conclusion that using any trading method, it is extremely difficult to take advantage of this impact. The impact of Mondays on Bitcoin returns was also verified by Caporale and Plastun (2018: 260). They demonstrated that it would have been advantageous to leverage this impact with the aid of a trading simulation. These results are in line with the research by Aharon and Qadan (2019: 420), who used OLS and GARCH models to demonstrate the day-of-the-week anomaly in Bitcoin volatility as well as returns.

This review of the literature highlights the significance of irrational investors' tendency to follow trends, exhibit sentiment, engage in herd behavior, and other biased behaviors while engaging in crypto transactions (Fousekis and Tzaferi, 2021: 18). Speculative-driven investors build their investing strategies on general and specific market inefficiencies and anomalies in order to maximize returns.

3.3 LITERATURE ON OVERREACTION FOR CRYPTOCURRENCIES

One of the financial market abnormalities that has been the most thoroughly studied is overreaction (Ball, 2009: 10). Only a few research, to our knowledge, have specifically addressed overreaction in the cryptocurrency market. An overreaction is typically defined in the empirical literature as a significant price change that partially reverts. The results of current empirical research are challenging to compare with one another since they use a range of modeling techniques and external factors, and they depend primarily on the choice of related elements.

By counting the amount of favorable and unfavorable words in an article, Karalevicius et al. (2018: 71) investigated the impact of articles about cryptocurrencies on the price of Bitcoin. Their findings imply a relationship between the price of bitcoin and media attitude. They also discovered that when news is released suddenly, investors tend to overreact.

Cryptocurrencies cannot be evaluated by certain fundamental values since they lack an intrinsic value. Only investor confidence and the coin's limited supply are variables that affect pricing. On the one hand, a return to the intrinsic value following an overreaction is improbable because it either does not exist or is extremely difficult to derive. The unavailability of fundamental values, on the other hand, might intensify irrational price fluctuations, and overreactions. Given the tremendous fluctuations of the cryptocurrency market, analyzing overreactions in this context is particularly fascinating. Compared to the FOREX or stock market, its average daily price volatility is up to 10 times higher (Caporale and Plastun, 2019: 1138). Caporale and Plastun (2019: 1139) used a series of parametric and non-parametric tests to study price patterns in the Bitcoin market. Their results indicate that countermovement after the overreaction is not profitable.

For the cryptocurrency pairs Bitcoin, Litecoin, Ripple, and Dash, Caporale and Plastun (2019: 1138) first modeled price overreactions as significant daily fluctuations in prices. They discovered that price fluctuations after overreactions are bigger than those after 'regular' price fluctuations. The fact that their results cannot be used for an advantageous trading strategy is an intriguing finding that is viewed as supporting the EMH (Caporale and Plastun, 2019: 1144). In order to comprehend how frequently there are price overreactions on the cryptocurrency market, notably in the instance of Bitcoin, Caporale et al. (2019: 112) conducted a study. They were able to attest to the possibility that the regularity of price overreactions might serve as a source of data for predicting price dynamics in the Bitcoin market.

In their 2020 paper, Borgards and Czudaj (2020, 4) put particular emphasis on the detection and frequency of overreactions in cryptocurrency markets. In order to evaluate twelve cryptocurrency markets for overreactions, Borgards and Czudaj (2020: 5) use a dynamic modeling technique. They discover that these markets have a

significant prevalence of price overreactions, which is compelling evidence in favor of the overreaction theory. In addition, their findings indicate that negative overreactions are more frequent than positive ones. Price overreactions are a significant financial market phenomenon that occurs during different economic circumstances because overreacting behavior is independent of data frequency.

Additionally, Corbet and Katsiampa (2020: 11) investigate the asymmetric pricing behavior for the price of Bitcoin and discover evidence of asymmetric reversion patterns at various frequencies. Similar to Borgards and Czudaj (2020: 44), they show that negative price returns have a larger tendency to revert when compared to positive returns, both in terms of reversing speed and intensity.

Chevapatrakul and V. Mascia (2019: 376) used quantile autoregressive models to look at the longevity of Bitcoin returns. They showed that investors overreact to sudden drops in the price of Bitcoin on a daily basis. They interpret this result as a result of market players panicking over negative sentiment and quitting the market, which led to a further decline in the price of bitcoin. On the other hand, when returns are positive on a weekly basis, investors seem to overreact and become too optimistic. As a result, the price of Bitcoin continues to grow when returns are positive on a weekly basis.

Tobias Kellner and Dominik Maltritz (2021: 1594) findings have several significant ramifications for both real-world trading and academic studies of market inefficiencies. The presence of considerable abnormal profit demonstrates the informational inefficiency of the crypto markets. The considerable market size effect demonstrates that smaller currency markets are less efficient than bigger currency markets. When anomalous returns are negative, they find overreactions, and when they are positive, they find underreactions. The authors also discovered evidence for a Magnitude effect, which indicates that greater initial abnormal returns are associated with higher inefficiencies. They have also found that price reactions after negative abnormal price changes are more intense. To conclude, herd effects, the actions of "noise" traders, various cognitive traps, biases, such as overconfidence and other behavioral patterns, insufficient liquidity, macroeconomic news releases, and the

application of technical analysis for investment choices can all contribute to abnormal returns.

Tianquan et. Al (2023: 1685) found that Before Bitcoin futures were introduced, there was a substantial momentum effect on the market. Momentum transformed into reversal effect once Bitcoin futures were introduced. The COVID-19 outbreak also resulted in a decrease in the reversal effect.

3.4 A REVIEW OF PREDICTION METHODS IN FINANCIAL MARKETS

Methods used to analyze the stock market can be categorized into four parts namely Technical analysis, Fundamental analysis, Discounted Cash flow analysis, and Sentiment Analysis.

In technical analysis, the past performance of the stock is taken into account using tools such as Time series analysis, Volume Analysis, Mean reversion and co-integration, Exponential Moving Average, and Stochastic Analysis. Results indicate that long-term trading seems to be more beneficial for profit-making (Joshi, 2014: 12). It has been shown that autoregression and logistic regression also work well (Garg, 2014: 613). It should be noted that price is the main indicator for the mentioned analysis tools and technical analysis does not predict what will happen in the future for the stock market.

The second method is fundamental analysis where the past performance of the company is taken into account. Methods used to this end include Regression analysis, Autocorrelation function, ANOVA, GARCH Models, Markov Chains, or any other Stochastic model (Krishnamoorthi and SASA, 2009: 117). The next method is called Discounted Cash Flow analysis in which the intrinsic value of a stock is taken into account. In this method, the future cash flow of the current investment will be considered. Sentiment Analysis is the last method where techniques such as web scraping methods help collect data to make investment decisions. Advanced AI with ML algorithms is employed in this type of analysis.

Machine learning tools have vast applications in stock market analysis. This includes different forms of artificial or deep neural networks implemented on various datasets transformed with tools such as principal component analysis. Other methods include decision trees, random forests, support vector machines, long short-term memory, and various classification and clustering methods (Gurav, 2018: 28).

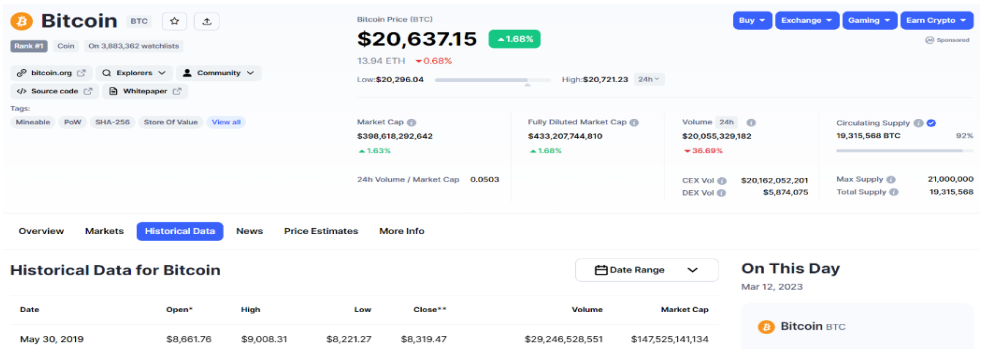
4 CHAPTER IV: METHODOLOGY AND DATA

The approach used to answer the key research questions in Chapter 1 is covered in this chapter. The main objective is to build an efficient framework under which the Overreaction Hypothesis (OH) is clearly studied from different perspectives. A tremendous effort has been made to make this framework strong both theoretically and in an applied sense.

4.1 DATA

The data for four cryptocurrencies (Bitcoin, Ethereum, Litecoin, and Ripple) was collected from (https://coinmarketcap.com/coins/). On this website, the price for a coin is calculated by taking the volume-weighted average of all reported market pair prices. The website's overview is shown in Figure 4-1

Figure 4-1: *CoinMarketCap* overview.



Source: Retrieved from www.*CoinMarketCap.com*.

4.2 STASTISTICAL TESTS

Statistical tests are essential tools used in data analysis to draw conclusions about a population based on sample data. They help researchers determine whether

observed differences or associations in the data are statistically significant or simply due to random chance. Two common statistical tests are the t-test and the Mann-Whitney U test (also known as the Wilcoxon rank-sum test).

The t-test is used to compare the means of two groups and determine if they are significantly different from each other. It assumes that the data follows a normal distribution, and the variances of the two groups are approximately equal. The t-test is widely used when dealing with continuous numerical data. There are two main types of t-tests which are Independent samples t-test and Paired samples t-test.

Independent samples t-test is used when the two groups being compared are independent of each other, meaning the data points in one group are unrelated to the data points in the other group. For example, comparing the test scores of students who attended different schools.

Paired samples t-test: This type of t-test is used when the two groups being compared are related or paired in some way. Each data point in one group is directly linked to a data point in the other group. For example, comparing the before and after test scores of the same group of students who underwent a specific intervention.

The null hypothesis for both types of t-tests is that there is no significant difference between the means of the two groups. If the p-value obtained from the t-test is below a predetermined significance level (commonly set at 0.05), then we reject the null hypothesis and conclude that there is a significant difference between the means of the two groups.

The Mann-Whitney U test is a non-parametric test used to compare the distributions of two independent groups. It does not assume that the data follows a specific distribution and is appropriate for ordinal or continuous data. This test is also used when the assumption of equal variances for the t-test is not met, or the data is not normally distributed.

The test works by ranking all the data points from both groups combined and then comparing the sum of ranks for each group. The null hypothesis states that there is no difference between the distributions of the two groups. If the p-value obtained from the Mann-Whitney U test is below the chosen significance level (often 0.05),

then we reject the null hypothesis and conclude that there is a significant difference between the distributions of the two groups.

Both the t-test and the Mann-Whitney U test are used to compare two groups, but the t-test is suitable for normally distributed data with equal variances, while the Mann-Whitney U test is appropriate for non-normally distributed data or when the assumption of equal variances is violated. When choosing between the two tests, researchers need to consider the nature of their data and the assumptions required by each test.

4.3 DATA AND DESCRIPTIVE ANALYSIS

The data for four cryptocurrencies was collected including the daily open and close prices from Aug 2017 to Aug 2022. These coins were BIT, ETH, LIT, and XRP. The reason behind choosing these cryptocurrencies was their higher market cap and market age. BIT and ETH have the highest market cap and popularity in the market whereas LIT and XRP have been in the market for several years and are thus suitable for the analysis. The return was calculated based on the following formula (Caporale and Plastun, 2020: 254):

$$R_i = \frac{Close_i - Open_i}{Open_i}$$

Eq. 4-1

Table 4-1 lists the summary statistics for the cryptocurrencies used in the present study.

Table 4-1: Summary statistics for BIT, LIT, ETH, and XRP.

BIT

	Close	Open	Return
Count	1827	1827	1827
Mean	19459.7	19470.35	0
Std	17345.97	17342.54	0.04
Min	3228.6	3228.7	-0.39
Q 25%	7117.4	7121.1	-0.02
Q 50%	9993	10031.6	0
Q 75%	33683.3	33681.05	0.02
Max	67528.7	67527.9	0.23

LIT

	Close	Open	Return
Count	1827	1827	1827
Mean	1070.11	1070.96	0
Std	1213.85	1213.85	0.05
Min	83.81	83.81	-0.45
Q 25%	209.6	209.62	-0.02
Q 50%	400.8	402.19	0
Q 75%	1792.16	1792.84	0.03
Max	4808.34	4808.38	0.26

ETH

	Close	Open	Return
Count	1827	1827	1827
Mean	1070.11	1070.96	0
Std	1213.85	1213.85	0.05
Min	83.81	83.81	-0.45
Q 25%	209.6	209.62	-0.02
Q 50%	400.8	402.19	0
Q 75%	1792.16	1792.84	0.03
Max	4808.34	4808.38	0.26

XRP

	Close	Open	Return
Count	1827	1827	1827
Mean	0.51	0.51	0
Std	0.36	0.36	0.07
Min	0.14	0.14	-0.42
Q 25%	0.26	0.26	-0.03
Q 50%	0.37	0.37	0
Q 75%	0.69	0.69	0.02
Max	2.78	2.78	0.86

We see a significant increase in coin prices. Figure 4-2 shows how close and open prices change over time for four cryptocurrencies BIT, LIT, ETH, and XRP. As the figure shows, the shape of the trend is similar for all of the cryptocurrencies where the price increases until 2020, and then it starts to decrease. Additionally, the price fluctuation is similar for pairs BIT-ETH and LIT-XRP.

Figure 4-2: Price change for BIT, LIT, ETH, and XRP.

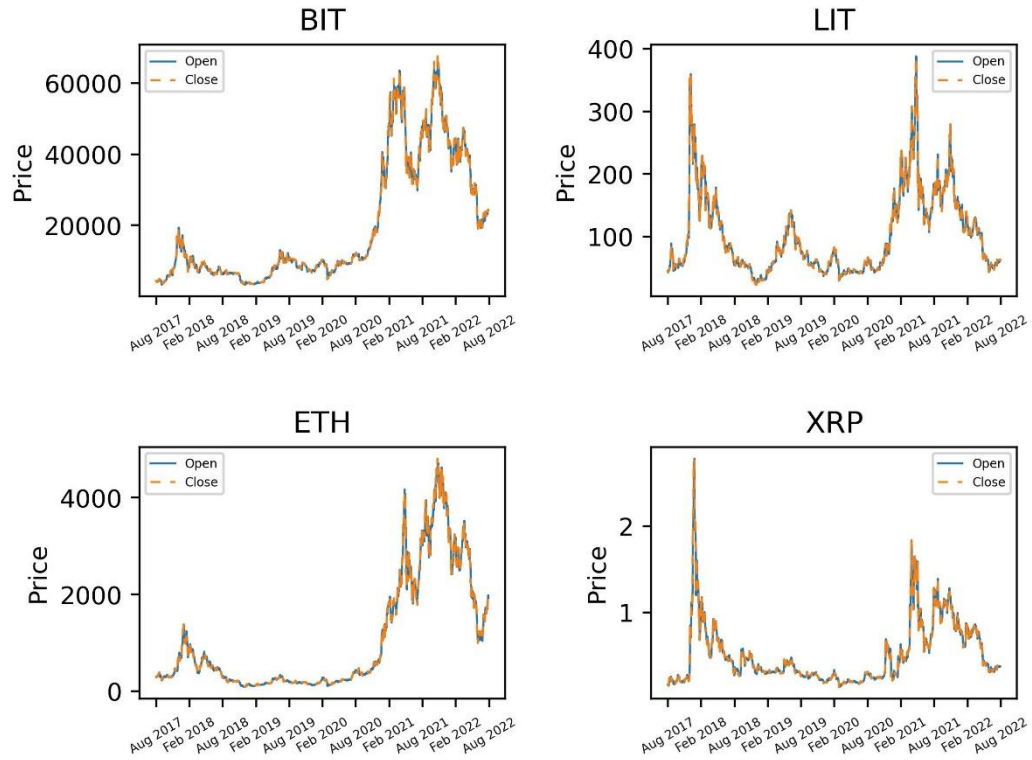
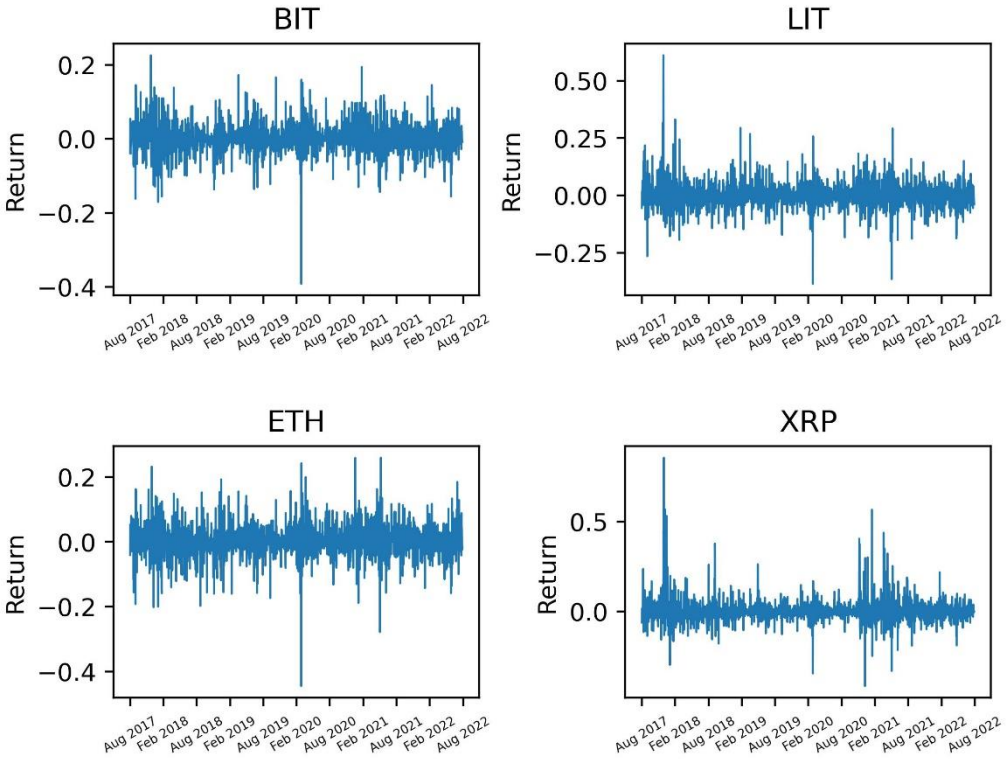


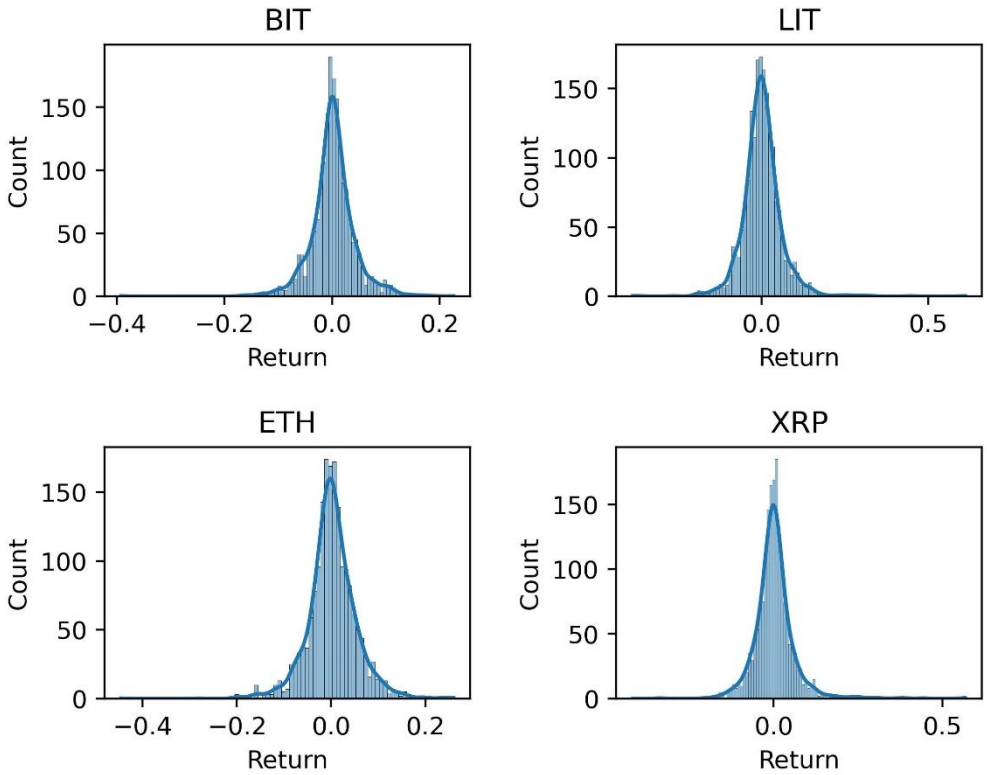
Figure 4-3 also shows the change in return for the cryptocurrencies of this research. As one sees, fluctuation in the return is lower for XRP because of the closeness of its close and open prices. However, the return change is almost the same for BIT, LIT, and ETH. Moreover, we see some sudden changes in return that can be investigated under the concept of Overreaction.

Figure 4-3: Return change for BIT, LIT, ETH, and XRP.



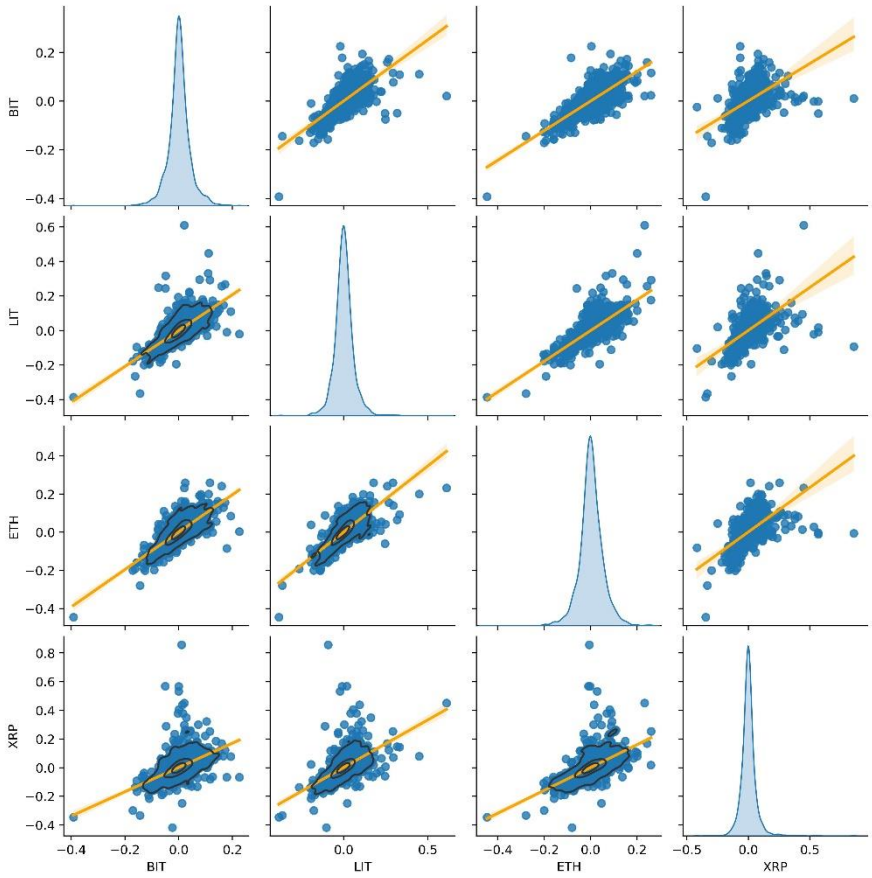
According to Figure 4-4, the density plot is depicted for all the four cryptocurrencies. Note that the plot is more toward zero and it slowly tends to infinity for higher returns. A probability density function (PDF), also known as the density of a continuous random variable, is a function used in probability theory that, for any given sample (or point) in the sample space (the range of possible values for the random variable), can be interpreted as expressing a relative likelihood that the random variable's value will be equal to that sample. Since a continuous random variable has an infinite number of possible values to begin with, the absolute likelihood that it will take on any particular value is 0, but the probability density (PDF) at two different samples can be used to estimate how much more likely it is that the random variable will be close to one sample than the other sample in any given draw.

Figure 4-4: Density plot for BIT, LIT, ETH, and XRP.



It is of higher value to see how returns for all the four cryptocurrencies change according to each other. In a pair analysis, it can be simply seen that there is a strong linear association between pair returns. Additionally, there is just a single cluster in all these plots. Figure 4-5 depicts plots.

Figure 4-5: Pair plot for returns of BIT, LIT, ETH, and XRP.



Another point of interest is to see the association of differences in returns. This is more like the concept of derivative. This analysis will be used later for further analysis. According to Figure 4-6, strong relationships can be seen in all of these pair analyses. Thus, there exists a positive relationship between the rate of returns.

Figure 4-6: Pair plot for the difference in returns of BIT, LIT, ETH, and XRP.

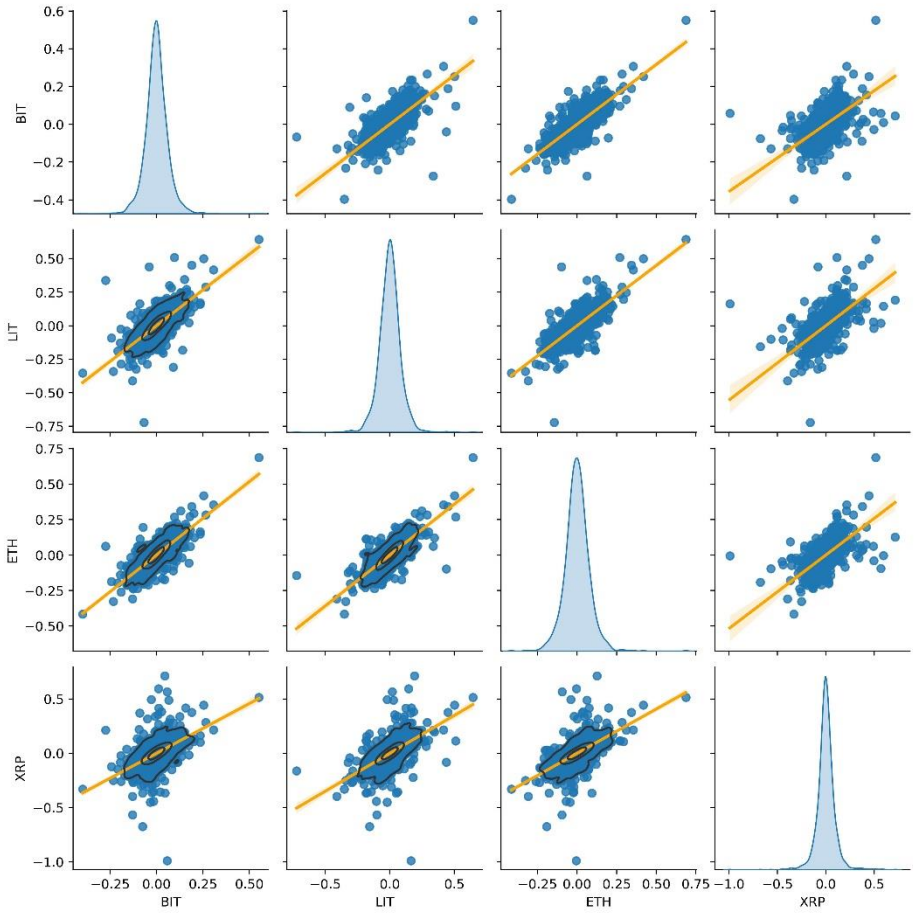
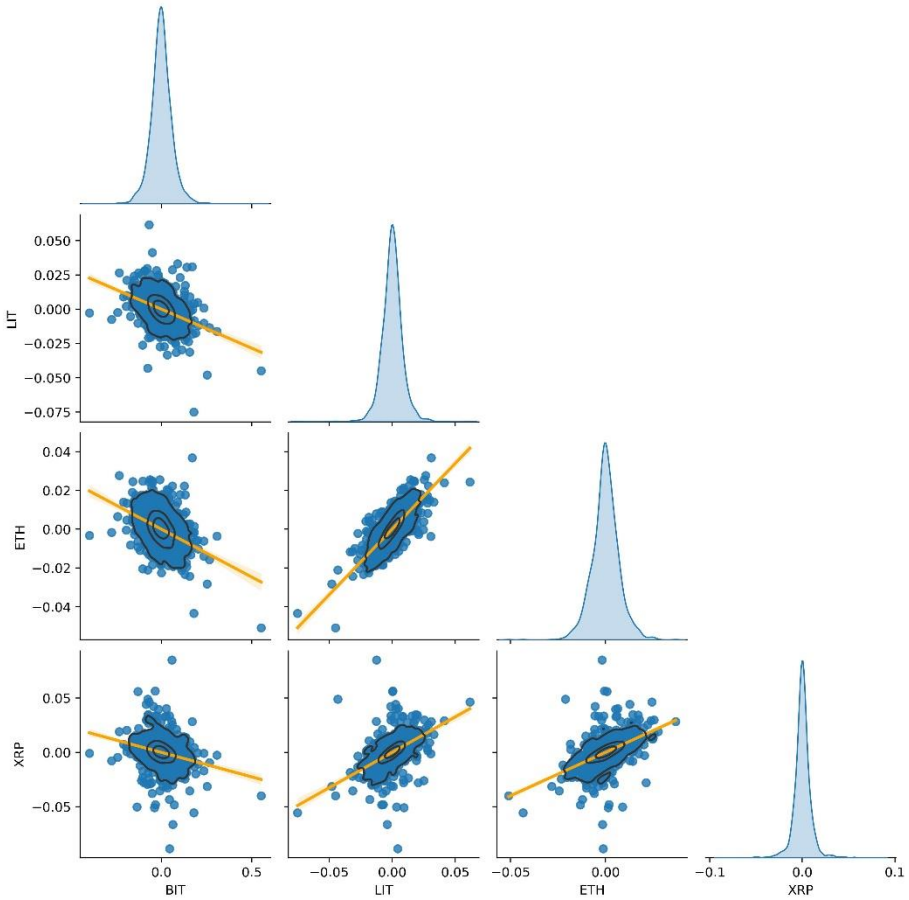


Figure 4-7 shows how the mean rate of return for the last 10 days for LIT, ETH, and XRP impacts the difference in return of BIT. As the figure shows, there exists a negative relationship between the rate of returns when incorporating the record of the last 10 days. Thus, the relationship exists with a lag of 10 days.

Figure 4-7: Pair plot for difference in returns of BIT, LIT, ETH, and XRP allowing the record of past 10 days in the form of a simple mean.



5 CHAPTER V: EMPIRICAL RESULTS

5.1 PRICE OVERREACTION

Note that an overreaction happens if (Caporale and Plastun, 2020: 256):

$$R_i = \frac{Close_i - Open_i}{Open_i}$$

$$(\text{Positive Overreaction}) \quad R_i > \bar{R}_i + k\sigma_R$$

$$(\text{Negative Overreaction}) \quad R_i < \bar{R}_i - k\sigma_R$$

$$\bar{R}_i = \frac{\sum_{j=i-20}^{i} R_j}{20}$$

Eq. 5-1

However, in this formula, we used a moving average with a length of 20 days for $\bar{R}_i$. In this formula, *k* stands for the number of standard deviations away from the mean $\bar{R}_i$. Note that higher returns are achievable when *k* increases. The reason behind choosing moving average 20 is three folds. First, the number is repeatedly used by traders to get a sense of the market for the past month. Second, using this number disregards the impact of the old market in our analyses. Third, there is not any significant difference between the moving average 20 compared to the moving average 50, 100,200 or even the average return of the whole period.

In this research, we assumed $k = 1$ as (Caporale and Plastun, 2020: 256) to get a balanced set of data. However, Table 5-2 shows the number of Overreactions for different values of *k*. According to this table, the number of Overreactions decreases as *k* increases. Additionally, the number of Overreactions during Aug 20 – Aug 21 seems to be higher. We implemented a hypothesis test, and the result is that the null hypothesis is rejected (p-value = 0.019, $n = 9$, statistic = 2.42) for equality of the number of Overreactions during this period and other periods. This however makes sense as returns during the pandemic are widely stressed by news and this in turn

increases the number of abnormal changes in returns. Moreover, the number of Overreactions seems to be higher for BIT, LIT, and ETH compared to XRP. However, the test results were not significant for various values of *k*. For different coins compared to XRP, we have the following results for $k = 1$ in Table 5-1. This result suggests that the market cap and popularity do not change the number of Overreactions for various coins.

Table 5-1: Comparing the number of Overreactions between XRP and the other three coins.

BIT-XRP

	Size	Mean	SD	Lower CI	Upper CI	t Statistic	t p-value	MW Statistic	MW p-value
BIT	10	49.9	6.2841	48.7481	51.0519	0.3794	0.7088	53.5	0.8197
XRP	10	48.8	6.0133	47.6977	49.9023				

LIT-XRP

	Size	Mean	SD	Lower CI	Upper CI	t Statistic	t p-value	MW Statistic	MW p-value
LIT	10	49.9	6.6851	48.6746	51.1254	0.367	0.7179	63.5	0.3245
XRP	10	48.8	6.0133	47.6977	49.9023				

ETH-XRP

	Size	Mean	SD	Lower CI	Upper CI	t Statistic	t p-value	MW Statistic	MW p-value
ETH	10	51.9	8.0554	50.4233	53.3767	0.9252	0.3681	62	0.384
XRP	10	48.8	6.0133	47.6977	49.9023				

Results are similar for different values of *k*.

Table 5-2: Number of Overreactions for different values of *k*.

K		Aug 17 - Feb 18	Feb 18 - Aug 18	Aug 18 - Feb 19	Feb 19 - Aug 19	Aug 19 - Feb 20	Feb 20 - Aug 20	Aug 20 - Feb 21	Feb 21 - Aug 21	Aug 21 - Feb 22	Feb 22 - Aug 22
k = 0.2											
	BIT	141	153	139	138	143	140	157	148	154	144
	LIT	141	147	147	147	149	146	148	146	161	155
	ETH	147	147	136	149	142	146	155	156	165	160
	XRP	147	145	135	145	146	143	139	149	151	155
k = 0.6											
	BIT	97	103	81	80	83	72	90	97	93	96
	LIT	91	90	91	85	89	85	94	95	92	99
	ETH	87	97	83	80	85	82	103	91	102	100
	XRP	87	98	74	80	91	87	84	84	88	93
k = 1											
	BIT	59	47	40	51	46	49	58	52	58	55
	LIT	56	50	55	38	49	48	58	53	59	59
	ETH	56	58	49	50	47	53	60	59	59	57
	XRP	50	50	42	46	43	48	51	45	53	51
k = 2											
	BIT	16	14	12	15	11	18	16	15	13	15
	LIT	18	11	14	13	15	17	12	14	15	14
	ETH	18	16	17	16	12	17	14	16	15	17
	XRP	22	17	17	11	13	17	15	12	13	14
k = 4											
	BIT	4	0	4	4	3	3	3	0	3	2
	LIT	7	1	3	2	5	2	3	3	1	1
	ETH	2	0	5	3	5	1	1	1	1	0
	XRP	4	0	6	4	4	4	3	4	3	0

Table 5-4 also shows the number of positive and negative Overreactions. As one sees, the number of Overreactions in BIT and ETH are higher mostly because of their higher popularity and market size compared to other coins. Also, the number of positive Overreactions seems to be higher than the number of negative Overreactions because of the increase in cryptocurrency prices during 2017 – 2022. However, the test results were not significant for this as shown in Table 5-3.

Table 5-3: Difference in the number of positive and negative Overreactions.

BIT

	Size	Mean	SD	Lower CI	Upper CI	t Statistic	t p-value	MW Statistic	MW p-value
# Pos. Over.	10	26.1	4.2767	25.316	26.884	0.4002	0.6942	53	0.8495
# Neg. Over.	10	25.4	3.0397	24.8428	25.9572				

LIT

	Size	Mean	SD	Lower CI	Upper CI	t Statistic	t p-value	MW Statistic	MW p-value
# Pos. Over.	10	26.4	4.2942	25.6128	27.1872	0.1541	0.8793	57.5	0.5938
# Neg. Over.	10	26.1	3.9611	25.3739	26.8261				

ETH

	Size	Mean	SD	Lower CI	Upper CI	t Statistic	t p-value	MW Statistic	MW p-value
# Pos. Over.	10	28.9	2.3	28.4784	29.3216	1.6604	0.1212	65	0.2709
# Neg. Over.	10	25.9	4.9082	25.0003	26.7997				

XRP

	Size	Mean	SD	Lower CI	Upper CI	t Statistic	t p-value	MW Statistic	MW p-value
# Pos. Over.	10	25.7	2.0025	25.3329	26.0671	3.1139	0.0065	83.5	0.0117
# Neg. Over.	10	22.2	2.7129	21.7027	22.6973				

Table 5-4: Number of positive (upper table) and negative (lower table) Overreactions.

k = 1	Aug 17 - Feb 18	Feb 18 - Aug 18	Aug 18 - Feb 19	Feb 19 - Aug 19	Aug 19 - Feb 20	Feb 20 - Aug 20	Aug 20 - Feb 21	Feb 21 - Aug 21	Aug 21 - Feb 22	Feb 22 - Aug 22
BIT	33	23	19	27	22	28	32	23	29	25
LIT	32	19	29	19	26	25	32	27	27	28
ETH	33	27	31	28	28	27	32	30	26	27
XRP	29	23	23	25	25	25	26	25	29	27

BIT	26	24	21	24	24	21	26	29	29	30
LIT	24	31	26	19	23	23	26	26	32	31
ETH	23	31	18	22	19	26	28	29	33	30
XRP	21	27	19	21	18	23	25	20	24	24

Financial markets were greatly affected by COVID-19. We tested this in this research. According to Figure 5-1, the price of a positive Overreaction seems to be

higher than the price of a negative Overreaction during the COVID-19 peak. We tested this using Mann-Whitney and t-tests, and the results indicated a significant difference for BIT according to Table 5-5. This is mostly because of the popularity and market cap for BIT which is higher than other coins. This characteristic of BIT makes it vulnerable to news during the pandemic causing many abnormal increases in return.

Table 5-5: Price of negative Overreactions vs. price of positive Overreactions during COVID-19.

BIT

	Size	Mean	SD	Lower CI	Upper CI	t Statistic	t p-value	MW Statistic	MW p-value
Price of Neg. Over.	54	30091.34	14237.19	29649.96	30532.72	-2.3064	0.0231	1079	0.014
Price of Pos. Over.	55	37003.17	16687.11	36495.4	37510.93				

LIT

	Size	Mean	SD	Lower CI	Upper CI	t Statistic	t p-value	MW Statistic	MW p-value
Price of Neg. Over.	56	138.1652	69.5538	136.0873	140.2432	-1.122	0.2647	1281	0.3608
Price of Pos. Over.	51	155.5885	87.5117	152.7128	158.4643				

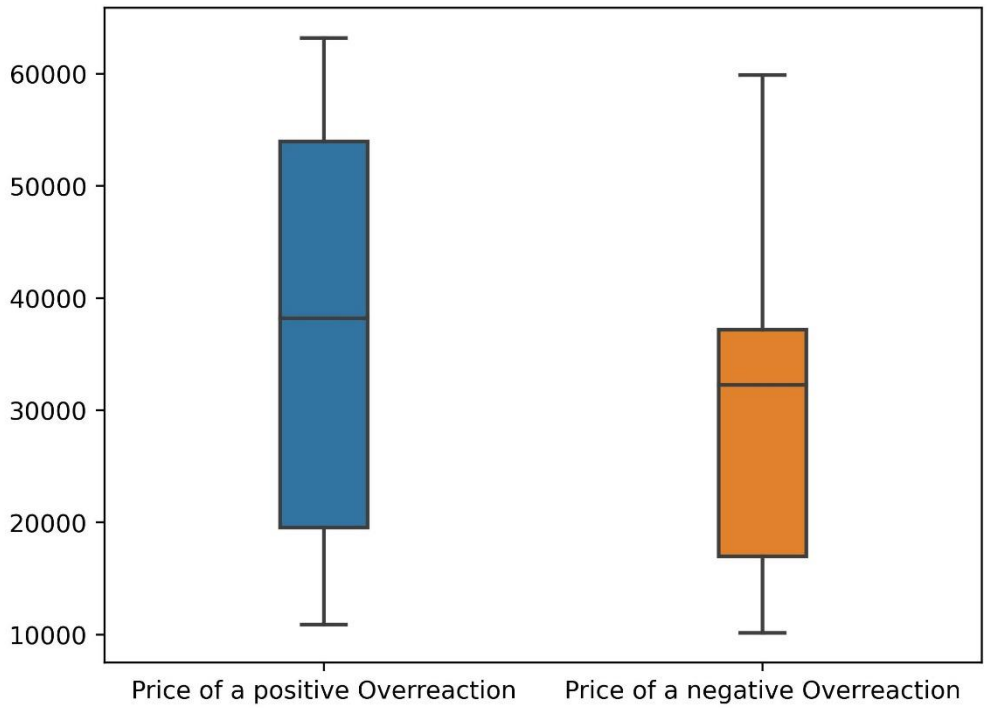
ETH

	Size	Mean	SD	Lower CI	Upper CI	t Statistic	t p-value	MW Statistic	MW p-value
Price of Neg. Over.	61	1381.652	926.5383	1356.276	1407.027	-1.0823	0.2815	1511	0.2837
Price of Pos. Over.	56	1586.523	1088.037	1554.017	1619.028				

XRP

	Size	Mean	SD	Lower CI	Upper CI	t Statistic	t p-value	MW Statistic	MW p-value
Price of Neg. Over.	52	0.4996	0.3028	0.4898	0.5093	-1.8719	0.0652	884	0.0564
Price of Pos. Over.	44	0.6494	0.445	0.6324	0.6664				

Figure 5-1: Prices of positive and negative Overreactions during the peak of COVID-19 for BIT.



The change in consecutive prices seemed to be higher during COVID-19 according to Figure 5-2. The result of Mann-Whitney and t-tests indicated a significant difference according to Table 5-6. This also makes sense because of the vulnerability of the cryptocurrency market to news during the pandemic.

Table 5-6: Change in price when Overreacting during COVID-19 and in ordinary days.

BIT

	Size	Mean	SD	Lower CI	Upper CI	t Statistic	t p-value	MW Statistic	MW p-value
Price change during COV.	92	2255.786	1560.911	2227.592	2283.98	7.5393	~0	29007	~0
Price change In ord. days	408	966.3152	1004.36	962.2569	970.3735				

LIT

	Size	Mean	SD	Lower CI	Upper CI	t Statistic	t p-value	MW Statistic	MW p-value
Price change during COV.	96	14.4139	14.9276	14.1556	14.6722	4.0706	0.0001	27386	~0
Price change In ord. days	403	7.8587	9.9786	7.8179	7.8995				

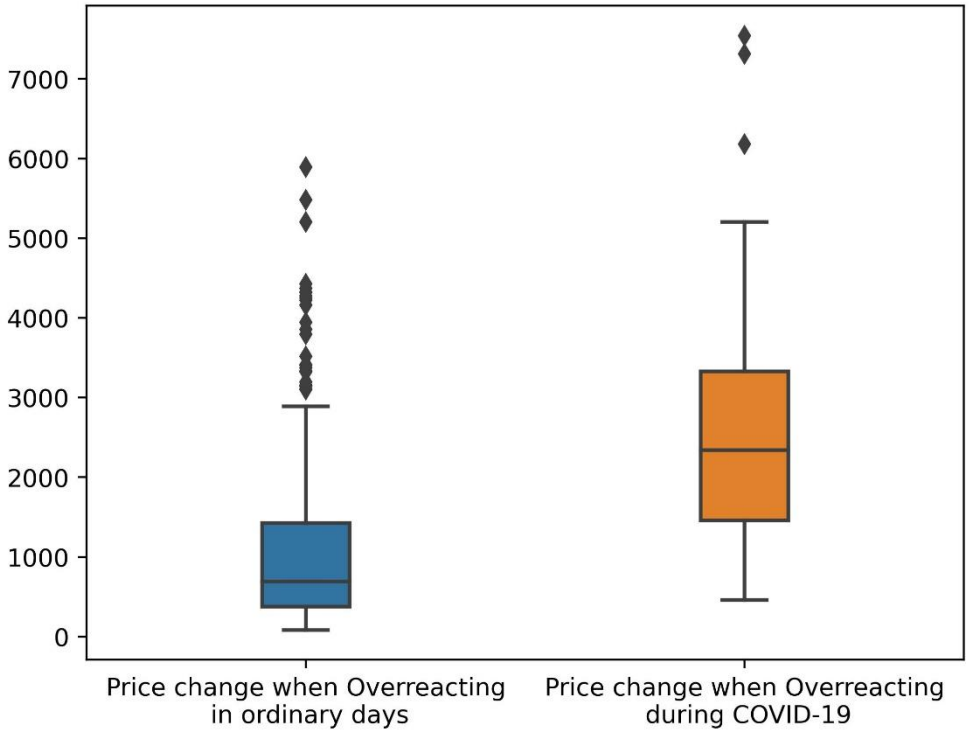
ETH

	Size	Mean	SD	Lower CI	Upper CI	t Statistic	t p-value	MW Statistic	MW p-value
Price change during COV.	102	135.1987	140.5969	132.9105	137.487	4.5258	~0	30309.5	~0
Price change In ord. days	418	68.9532	87.919	68.6064	69.2999				

XRP

	Size	Mean	SD	Lower CI	Upper CI	t Statistic	t p-value	MW Statistic	MW p-value
Price change during COV.	87	0.0766	0.0942	0.0748	0.0784	3.3501	0.0011	20637.5	0.0095
Price change In ord. days	403	0.0412	0.0593	0.0409	0.0414				

Figure 5-2: price change during and out of the COVID-19 peak for BIT.



According to Table 5-8, another point is that overreaction can be seen in all daily, weekly, and monthly time points. According to this table, the number of weekly Overreactions is expectedly higher than monthly ones. If we multiply the number of monthly Overreactions by 30/7 and subtract the corresponding monthly Overreaction, we expect to get the number of weekly Overreactions. We tested this using a *t* test and the results for different coins were according to Table 5-7.

Table 5-7: Observed and predicted number of weekly Overreactions for all cryptocurrencies.

BIT

	Size	Mean	SD	Lower CI	Upper CI	t Statistic	t p-value	MW Statistic	MW p-value
Observed	10	8.9	3.015	8.3473	9.4527	-0.6116	0.5487	40	0.4683
Predicted	10	9.8571	3.5993	9.1973	10.5169				

LIT

	Size	Mean	SD	Lower CI	Upper CI	t Statistic	t p-value	MW Statistic	MW p-value
Observed	10	6.8	1.9391	6.4445	7.1555	-0.7939	0.4377	39	0.4208
Predicted	10	7.5571	2.1039	7.1715	7.9428				

ETH

	Size	Mean	SD	Lower CI	Upper CI	t Statistic	t p-value	MW Statistic	MW p-value
Observed	10	8	1.8974	7.6522	8.3478	-2.1992	0.0417	29	0.1173
Predicted	10	10.1857	2.3	9.7641	10.6073				

XRP

	Size	Mean	SD	Lower CI	Upper CI	t Statistic	t p-value	MW Statistic	MW p-value
Observed	10	6.2	2.8566	5.6764	6.7236	-0.4265	0.6753	39	0.4233
Predicted	10	6.9	4.0107	6.1648	7.6352				

As one sees, because of insignificant results, Overreactions happen at the same rate in both monthly and weekly time points.

Table 5-8: Number of weekly and monthly Overreactions.

K=1	Cryptocurrency	Aug 17 - Jan 18	Jan 18 - Aug 18	Aug 18 - Jan 19	Jan 19 - Aug 19	Aug 19 - Jan 20	Jan 20 - Aug 20	Aug 20 - Jan 21	Jan 21 - Aug 21	Aug 21 - Jan 22	Jan 22 - Aug 22
Weekly Overreaction											
	BIT	15	7	5	11	7	6	11	8	12	7
	LIT	7	4	6	7	9	4	10	6	9	6
	ETH	11	7	9	6	10	5	10	6	8	8
	XRP	6	1	1	6	9	9	8	7	6	9
Monthly Overreaction											
	BIT	4	4	1	4	3	3	4	3	3	1
	LIT	3	2	2	2	3	2	3	2	3	1
	ETH	4	3	2	4	3	2	3	3	4	3
	XRP	3	0	1	3	1	2	4	3	1	3

5.2 PRICE OVERREACTION ACCORDING TO A NEW DEFINITION OF RETURN

According to Caporale and Plastun (2018: 1140), there should be either a price correction or a price movement in the overreaction direction a day after an Overreaction occurred. Here we hypothesize that counter-reactions after an Overreaction differ from those on normal days. To this end, we define a return as follows:

$$R_i = \frac{High_i - Low_i}{Low_i}$$

We define Overreaction the same way we defined it in the previous section. Besides this, we define a counter-reaction (CR) during the next day according to the following formulas:

$$R_{i+1} = \frac{Open_{i+1} - Low_{i+1}}{Low_{i+1}} \quad \text{when price is increasing}$$

$$R_{i+1} = \frac{High_{i+1} - Open_{i+1}}{Open_{i+1}} \quad \text{when price is decreasing}$$

Eq. 5-2

We tested the CR hypothesis for all four coins and the results are summarized in Figure 5-3 and Table 5-9. According to this table, significant results suggest that CR happens more intensely after an Overreaction occurred.

Similarly, according to Caporale and Plastun (2018: 1140), price movement (PM) can be defined in the same way except the formulas in Eq. 5-2 are used differently when prices increasing or decreasing. Results for PM are also significant when an Overreaction happens.

Table 5-9: CR a day after an Overreaction vs. normal days.

BIT

	Size	Mean	SD	Lower CI	Upper CI	t Statistic	t p-value	MW Statistic	MW p-value
CR after Over.	1563	0.0119	0.0134	0.0119	0.0119	-5.4061	~0	151923	~0
PM in Ord. days	263	0.0209	0.0264	0.0207	0.0211				

LIT

	Size	Mean	SD	Lower CI	Upper CI	t Statistic	t p-value	MW Statistic	MW p-value
CR after Over.	1544	0.0231	0.0344	0.0231	0.0232	-4.3504	~0	166318	~0
PM in Ord. days	282	0.0373	0.0527	0.037	0.0376				

ETH

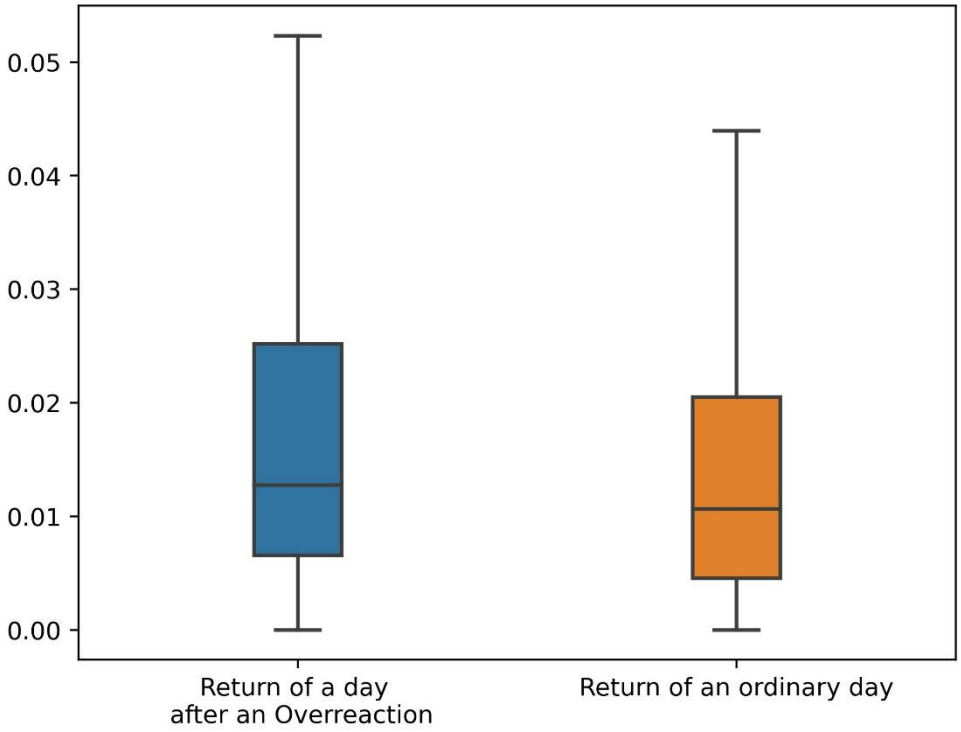
	Size	Mean	SD	Lower CI	Upper CI	t Statistic	t p-value	MW Statistic	MW p-value
CR after Over.	1533	0.0189	0.0223	0.0189	0.0189	-6.2593	~0	165612.5	~0
PM in Ord. days	293	0.033	0.0372	0.0328	0.0332				

XRP

	Size	Mean	SD	Lower CI	Upper CI	t Statistic	t p-value	MW Statistic	MW p-value
CR after Over.	1552	0.0247	0.0406	0.0246	0.0247	-4.8945	~0	147130	~0
PM in Ord. days	274	0.0472	0.074	0.0467	0.0476				

CR can be seen in the BIT market according to Figure 5-3.

Figure 5-3: CR after an Overreaction and in normal days.



5.3 COMPARING THE TWO DEFINITIONS FOR RETURN

Both definitions stated in Eq. 5-1 and Eq. 5-2 have been used to describe a return. Since the definition in Eq. 5-2 takes into account the highest and lowest prices, it seems to better count the number of Overreactions; however, it lacks to account for negative Overreactions and just considers the positive ones. In this section, we hypothesize that the number of positive Overreactions taken from Eq. 5-1 is the same as the number of Overreactions taken from Eq. 5-2 according to Table 5-10. To this end, we run the two tests mentioned in previous sections to see if there is a difference. Results in Table 5-11 suggest that the is no difference between them indicating that both definitions can be safely used to count the number of Overreactions.

Table 5-10: The number of positive Overreaction taken from Eq. 5-1, and the number of Overreactions taken from Eq. 5-2.

Cryptocurrency	Aug 17 - Jan 18	Jan 18 - Aug 18	Aug 18 - Jan 19	Jan 19 - Aug 19	Aug 19 - Jan 20	Jan 20 - Aug 20	Aug 20 - Jan 21	Jan 21 - Aug 21	Aug 21 - Jan 22	Jan 22 - Aug 22
BIT	32	23	20	29	24	24	33	27	20	30
LIT	32	24	26	27	28	29	29	31	27	29
ETH	27	30	29	27	24	33	30	32	30	30
XRP	29	27	27	24	24	31	34	25	22	31

BIT	33	23	19	27	22	28	32	23	29	25
LIT	32	19	29	19	26	25	32	27	27	28
ETH	33	27	31	28	28	27	32	30	26	27
XRP	29	23	23	25	25	25	26	25	29	27

Table 5-11: A set of statistical tests to assess the difference between the number of positive Overreaction taken from Eq. 5-1 and the number of Overreactions taken from Eq. 5-2 for all coins.

BIT

	Size	Mean	SD	Lower CI	Upper CI	t Statistic	t p-value	MW Statistic	MW p-value
HL	10	26.2	4.4677	25.381	27.019	0.0485	0.9618	52	0.9094
OC POS	10	26.1	4.2767	25.316	26.884				

LIT

	Size	Mean	SD	Lower CI	Upper CI	t Statistic	t p-value	MW Statistic	MW p-value
HL	10	28.2	2.2271	27.7917	28.6083	1.1163	0.2837	61.5	0.4009
OC POS	10	26.4	4.2942	25.6128	27.1872				

ETH

	Size	Mean	SD	Lower CI	Upper CI	t Statistic	t p-value	MW Statistic	MW p-value
HL	10	29.2	2.4819	28.745	29.655	0.266	0.7933	55	0.7295
OC POS	10	28.9	2.3	28.4784	29.3216				

XRP

	Size	Mean	SD	Lower CI	Upper CI	t Statistic	t p-value	MW Statistic	MW p-value
HL	10	27.4	3.6111	26.738	28.062	1.2351	0.237	62	0.3791
OC POS	10	25.7	2.0025	25.3329	26.0671				

In this section, we also want to see the price change after an Overreaction during COVID-19 and out of the pandemic. According to Table 5-12, we get the same significant result when using the formula stated in Eq. 5-2. This confirms that both definitions can be used to study the Overreaction Effect. Additionally, Figure 5-4 shows this significant difference for BIT.

Table 5-12: Price change when overreacting in and out of the pandemic using the formula stated in Eq. 5-2.

BIT

	Size	Mean	SD	Lower CI	Upper CI	t Statistic	t p-value	MW Statistic	MW p-value
During COV	60	4089.0567	2811.2315	4010.7595	4167.3538	6.1561	0	9420	0
Out COV	204	1716.4554	1720.9742	1702.5155	1730.3952				

LIT

	Size	Mean	SD	Lower CI	Upper CI	t Statistic	t p-value	MW Statistic	MW p-value
During COV	59	28.7675	25.3515	28.0492	29.4857	3.3828	0.0011	9442.5	0
Out COV	223	16.454	21.9418	16.2915	16.6166				

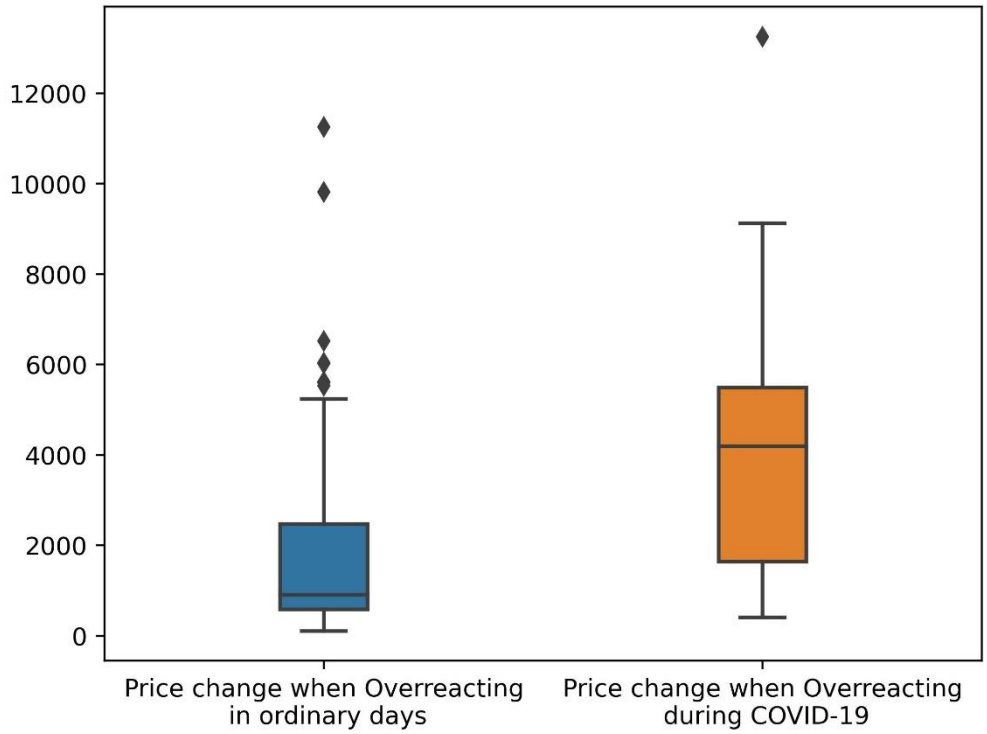
ETH

	Size	Mean	SD	Lower CI	Upper CI	t Statistic	t p-value	MW Statistic	MW p-value
During COV	61	263.2966	256.9975	256.258	270.3351	4.0584	0.0001	10272	0
Out COV	232	122.8303	149.7963	121.7639	123.8966				

XRP

	Size	Mean	SD	Lower CI	Upper CI	t Statistic	t p-value	MW Statistic	MW p-value
During COV	60	0.1521	0.1492	0.148	0.1563	3.4781	0.0008	7999	0.0036
Out COV	214	0.0804	0.1008	0.0796	0.0812				

Figure 5-4 Price change when overreacting in ordinary days vs. during the pandemic when using the formula stated in Eq. 5-2.



DISCUSSION

More digital currencies have arisen during the past several years since the first cryptocurrency, known as Bitcoin, initially appeared on the financial markets in 2008. We can establish that the emergence of cryptocurrencies and the ease of trading in digital currencies on financial markets have been made possible by cutting-edge technology, which has contributed to this exponential expansion. Today's cryptocurrency market hosts more than 25,636 cryptocurrencies, but Bitcoin—which accounts for more than 47.7% of the market capitalization—remains the pioneer of the digital currency world.

Because cryptocurrencies are still an early-stage asset class in the financial markets, investors may not be completely aware of how to assess and trade cryptocurrencies. This might account for the price overreaction seen in the cryptocurrencies under examination. Therefore, in this study, we examine the existence of overreaction in the prices of some selected cryptocurrencies such as Bitcoin, Ethereum, Ripple, and Litecoin, the four cryptocurrencies with the largest market caps and the longest history in the financial markets by using daily data for the period between 15.08.2017-15.08.2022. Theoritically, the existence of overreaction indicates that market is informationally inefficient according to Fama (1970).

Defining Overreaction as considerable changes in return, we tested the data for different threshold levels and chose the one that resulted in a balanced dataset. In this definition, we calculated the average return using a moving average with a length of 20 days to remove the effects of the old days. We observed that the number of Overreactions decrease when we increase the threshold according to the definition. This confirms the validity of the procedure taken in this analysis. Additionally, we observed that the number of positive Overreactions was slightly greater than the number of negative Overreactions; however, this finding was not statistically significant. One cause behind this would be the increasing price of cryptocurrencies during 2017-2022.

With a focus on the COVID-19 pandemic's effects, the current study also examines the overreaction behavior of four cryptocurrencies using intraday data. The

following are our primary conclusions. During the Covid-19 epidemic, overreactions occur more often and with greater intensity. We implemented a statistical hypothesis test and concluded that the null hypothesis was rejected for the equality of the number of Overreactions in and out of the COVID-19 peak. Additionally, the change in price was more dramatic during this period and was statistically confirmed using one parametric and one non-parametric test. Investment professionals, portfolio managers, and decision-makers should consider the results of this section.

Our findings contradict the Efficient Market Hypothesis (EMH). The existence of price overreactions indicates that the cryptocurrency market is not efficient, which allows investors and portfolio managers to take advantage of price overreactions to create appropriate investment strategies and boost the performance of investments. Additionally, because the cryptocurrency market exhibits price overreaction behavior, traders and fund managers must continuously and often track changes in the market's price dynamics in order to adjust their investment plans as necessary.

This discovery could make it easier for portfolio managers and investors to predict how cryptocurrencies would act during future lockout or crisis situations. This finding implies to policymakers that governments should prepare to deal with these shocks in the years to come while taking social and environmental hazards into account. We repeated the analysis for different points including week and month. We showed that the overreaction effect is visible and can be statistically confirmed in these cases too. In other words, the prevalence of the overreaction is not subject to the time point at which we analyze the data. We observed that the number of Overreactions under different time points is proportionally distributed in a particular time window meaning that the number is higher for day and lower for month.

We also found that the price for positive Overreactions is higher than the price for negative Overreactions during the pandemic indicating that during this period, the market is stressed by news mostly causing positive price changes. Additionally, the presence of price overreaction behavior in the cryptocurrency market also implies that investors and portfolio managers need to monitor its price dynamics regularly, and at high frequency, to be able to adapt their investment strategies accordingly. This finding might help investors and portfolio managers to better anticipate the behavior of

cryptocurrencies in potential future lockdown or crisis periods. For policymakers, this result suggests that governments should anticipate such shocks in the future while taking into account social and environmental risks.

Since there is no consensus on the definition of an Overreaction, we used a definition based on High-Low prices alongside Close-Open prices. Results suggest that both counter reactions and price movements in the direction of overreaction, happen more intensely after an Overreaction occurred. We later implemented two statistical tests to compare the performance of the two formulas used to define an Overreaction. Both tests significantly confirm that both formulas can be safely used to study the Overreaction effect.

Future studies may examine the overreaction hypothesis for different types of assets that can be compared using the same standards and methodology since we have conclusively shown that it holds for a variety of cryptocurrencies. Developing methods that are even more suited to detecting pivot points beforehand and so enabling those who invest to achieve higher gains is another intriguing area for future study.

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