THE REPUBLIC OF TURKEY
BAHCESEHIR UNIVERSITY

COGNITIVE BIASES OBSERVED AMONG CRYPTOCURRENCY INVESTORS

Master's Thesis

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ISTANBUL, 2019

THE REPUBLIC OF TURKEY
BAHCESEHIR UNIVERSITY

INSTITUTE OF SOCIAL SCIENCES
CAPITAL MARKETS AND FINANCE PROGRAM

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T.C. BAHCESEHIR UNIVERSITY

INSTITUTE OF SOCIAL SCIENCES

Capital Markets and Finance ....MASTER'S PROGRAM

Title Of The Thesis: Cognitive biases observed among crypto currency investo

Name and Surname Of The Student : Günel Musayeva

Thesis Defence Day : 21. 05. 2019

This thesis has been approved by the Institute of Social Sciences which has fulfilled the necessary conditions as Master thesis.

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I certify that this thesis has fulfilled the necessary requirements as Master thesis.

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This thesis was read by us, quality and content as a Master's thesis has been seen and accepted as sufficient.

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DEDICATION

I would like to demonstrate my considerably profound gratitude to my parents and to my dear friends for always providing me invaluable support and unceasing encouragement throughout my education period. I have been continuously motivated through the researching and writing process of this thesis and through the completion of this Masters' degree. This accomplishment would not have been possible without their moral support.

I want to dedicate this study to my father Elshad MUSAYEV and to my mother Firuza MUSAYEVA. They have been the most outstanding parents and supporters who have guided me with their invaluable remarks throughout my academic and personal life.

ACKNOWLEDGEMENT

I want to thank my thesis advisor Prof. Dr. Umit EROL, the faculty member of the Faculty of Economics, Administrative and Social Sciences at Bahcesehir University for his precious remarks and encouragement through the process of writing this thesis. Thanks to classes I have taken from him during my bachelor's and master's education, I had a chance to improve my knowledge both in economic and financial analysis. Especially his thorough knowledge in derivatives market has encouraged me for further research about the subject.

ABSTRACT

COGNITIVE BIASES OBSERVED AMONG CRYPTOCURRENCY INVESTORS

Gunel Musayeva

Capital Markets and Finance Master's Program

Thesis Advisor: Prof. Dr. Umit Erol

May, 2019, 63

This paper is written as a master's thesis that generally provides descriptive analysis on 4 cryptocurrencies and 4 indexes and according to similarities observed among stock investors and crypto investors, it provides literature review about the concept and testing of these cognitive biases; some of which are overconfidence, anchoring and representativeness heuristic. The great deal of analysis has been conducted on cognitive biases' effect on investors. Nonetheless, there are a few research written about cognitive biases observed among cryptocurrency investors. The concept of cognitive bias is highly crucial in the sense that unintentional use of cognitive biases in decision making process can have detrimental effects on investor's portfolio; thereupon, mostly observed biases should be illustrated by researchers to investors so that they can try to eliminate those unconscious inclinations during their decision making process. On the other hand, analyzing cognitive biases in cryptocurrency market is considerably vital due to the lack of coherent information in the market and limited knowledge of investors. Despite being very significant and beneficial analysis, there are huge constrictions in assessment of the biases due to privacy and anonymity of investors. Therefore, in this thesis, the comparison of index and cryptocurrency price distribution is analyzed to show the fact that the samples are not normally distributed. Lastly, observed similarities in these samples help to conclude that the similar biases observed in stock markets can be valid for cryptocurrency investors, as well.

Keywords: Cognitive biases, Cryptocurrency, Bitcoin, Ethereum, Litecoin

ÖZET

KRIPTOPARA YATIRIMCILARINDA GÖZLEMLENEN
BİLİŞSEL SAPMALAR

Günel Musayeva

Sermaye Piyasaları ve Finans Yüksek Lisans Programı

Tez danışmanı: Prof.Dr. Ümit Erol

Mayıs, 2019, 63

Hisse senedi yatırımcılarında bir çok bilişsel sapmalar gözlemleniyor. Hangi bilişsel sapmaların genel olarak gözlemlendiğini bildikleri ve buna göre geri dönüşler aldıkları zaman yatırımcıların portfolyo performanslarında önemli ölçüde pozitiv ilerleme kaydediliyor. Fakat bilişsel sapmaların analiz edilmesi ülkelerin sermaye piyasaları düzenlemeleri ve yatırımcı gizliliği sebebiyle çok zordur ve gerekli veriye her kesin ulaşması mümkün olmadığından bilişsel sapmalar üzerine az sayıda sayısal analiz yapılmıştır. Benzer durum kriptopara yatırımcıalrında da gözlemleniyor. Aslında bilgi paylaşımı daha sınırlı olduğundan ve doğru bilgiye ulaşmak daha zor olduğundan kriptopara yatırımcılarında daha çok bilişsel sapmalara rastlamak mümkündür. Sayısal analizin yapılabilmesi için farklı piyasaların sağladığı verilere ulaşmak mümkündür, fakat bu fiyat verilerinin kodlarla ifade edildiği dikkate alındığında analiz için daha geniş bir zaman dilimine ihtiyaç duyuluyor. Bu tezin amacı 4 kriptopara ve 4 index fiyatlarına göre deskriptif analiz yaparak hisse senedi yatırımcılarında gözlemlenen temel bilişsel sapmaların aslında kriptopara yatırımcılarında da gözlemlenebilmesini açıklamaktır. Bu sayede kriptopara yatırımcıları işlem yaparken daha dikkatli olabilir ve sonuçta portfolyo performanslarını iyileştirebilirler.

Anahtar kelimeler: Bilişsel Sapma, Kriptopara, Bitcoin, Ethereum, Litecoin

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ABBREVIATIONS

BTC	:	Bitcoin
BIST30	:	Borsa Istanbul 30
BIST100	:	Borsa Istanbul 100
ETH	:	Ethereum
LTC	:	Litecoin
S&P500	:	Standard and Poor’s 500 Index
XRP	:	Ripple

1. INTRODUCTION

Academicians generally tend to understand and evaluate the stock prices along with their behavior and models that have been established on the standard risk return of stock prices. Namely, the CAPM (Capital Asset Pricing Model) depends on the hypothesis that prices are normally distributed and behavior of prices is random walk. Investors, on the other hand, design trading strategies by taking into account the price persistence in the short run or mean reversion in the long run. Majority of the prominent models in financial analysis assume price distribution as normal and they also assume that people act rationally. However, decisions made by people are not always logical. Indeed, even though it is generally assumed any deviation from logical decision-making process is haphazard, those deviations are continuously observed and thus, systematic. If an example should be given, people are more inclined to overestimate their ability to drive. Nonetheless, if such deviation was by chance, they could underestimate their driving skills (Svenson 1981). In other words, even though main finance or economics theories are on the base of the premise that people are rational, they are not. Therefore, such systematic deviations from logical or rational decision provides considerable foundation for behavioral finance or economics to decrease conventional principal rules of financial economics. (Barber and Odean 1999).

Caporale and Plastun (2018) emphasize that the chief paradigm used in financial economics is the Efficient Market Hypothesis (EMH). The cardinal premise provided by Fama in 1965 is that asset prices are unpredictable. However, there are some behavioral factors that may lead to short-run predictability in the prices. For instance, according to Akerloff and Schiller (2009), cognitive biases play crucial role in predictability of asset prices. On one hand, difference in investment horizons can be a tool to make some assumptions about prices. (Campbell and Viceira 2002). On the other hand, noise traders according to Black (1985) can be another medium to estimate prices. Moreover, as stated by Taylor and Allen (1992) technical analysis tools can be a good guide to estimate price movements. Even some tools used in technical analysis is thought to be valid for most of the certain cases. Psychologists have classified several techniques to illustrate how people do not make rational decisions or how their optimal judgements deviate from rationality. According to Barber and Odean (1999) behavioral finance enables researchers to incorporate such deviations in human behavior and compromise those deviations in financial theories.

Also, Poyser (2018) extrapolates that the behavioral economics uncover systematic deviations from rationality. He sees individuals as prey and he says any market inefficiency or anomaly observed in finance world is related with human beings' cognitive biases. As mentioned by Tokarchuk (2017), behavioral biases are classified into two types: cognitive and emotional. The influence of the both can negatively affect the rationality of your decisions. The purpose of this research is to analyze the impact on investment decision of such factors in the context of cryptocurrency market. Lam (2018) clarifies the term "cryptography" as a field that involves variety of methods to secure notion or information from untoward intrusion or unauthorized control by a third party. Cryptocurrency market is booming and is a very attractive investment opportunity also characterized by unpredictable behavior and several speculations. (Tokarchuk and Donkohlova 2017). Individuals face with biased decision-making environment due to a great number of pseudoscientific articles and forecasts.

According to Poyser (2018), cryptocurrency markets resemble several methods on financial markets showed by behavioral finance supporters. The digital world is leading to an increase in state-of-art ideas' exposure and variations and opportunities in economics paradigms. Cryptocurrencies as well as Blockchain technology are concepts that have emerged by the evolution of the "new economy". One can say that Bitcoin created a big amount of interest since it was not the first, but the most prosperous presentation of a peer to peer network. On the other hand, extreme upswings in prices and volatility also attracted good deal of responsiveness from the public and this responsiveness is shared by other unconventional coins such as Ripple, Ethereum, Litecoin as well as Initial Coin Offering (ICO). Behavioral finance research tries to explain why investors in stock markets behave irrationally. Poyser (2018) claimed the puzzle of cryptocurrencies market prices can be explicated by a behavioral finance aspect since traders illustrate cognitive biases which have an essential position in the explanation of the volatility of prices. His paper starts with a literature review and a data analysis which focus on theoretical and empirical evidence showing that investors' actions are not aligned with rationality concept and this is how the crypto-market problem can be explained. ((Kahneman and Riepe 1998), (Friedman and Rubinstein 1998), (Conlisk 1996), (Akerlof and Yellen 1985) and (Simon 1982)).

Despite the fact that there is a considerable number of studies about market overreactions ((Caporale et al. 2017), (Mynhardt and Plastun 2013), (Bremer and Sweeney 1991), (Choi and Jayaraman 2009), (Ferri and Min 1996), (Atkins and Dyl 1990), (Brown et al. 1988) and (De Bondt and Thaler 1985) and some others), few researchers concentrated on the cryptocurrency market despite the fact that it is one of the most volatile market compared to other financial securities markets. The amplitude of average daily prices in the cryptocurrency market is almost ten times higher compared to foreign exchange market. Also, capacity of cryptocurrency market is seven times greater than stock markers and almost five times greater than markets where various commodities are traded. It also is a young but prominent market rendering the analysis of overreactions and price anomalies in that market more meaningful.

The research in cognitive biases of cryptocurrency markets is very few. Some researchers analyzed one cryptocurrency only which is Bitcoin and others limited the scope of the research to one specific bias. However, no quantitative research which is based on financial data has considered three different cognitive biases among 4 cryptocurrency investors. The study here is also a unique analysis since it covers descriptive analysis of price data for 4 cryptocurrencies and 4 indexes which illustrate anomalies in decision making process.

The plan is to identify the past performance of cryptocurrency investors to see if they invest in cryptocurrencies when they observe the latest run-ups, which can be an indication of the extrapolation bias. Indeed, it is an instance of the representativeness bias. Also, the thesis tries to check if other cognitive biases are possible to be observed among cryptocurrency investors. Therefore, it is also aimed to provide a normality check for both specific indexes and cryptocurrencies in order to show irrational decision making by reference to the distribution of the prices. If the price samples are not normally distributed with all cryptocurrencies and indices displaying the similar characteristics, then the theories based on irrational decision-making explicating the cognitive biases can be assumed to be valid for both categories. To be more precise, in this thesis, it is assumed that the cognitive bias is a crucial issue. People must be informed at this point that they maybe presented such anomalies during their investment decisions and so by taking some actions against those biases, their portfolio performance can be ameliorated. It is also worth noting the prominence and attractiveness of cryptocurrencies as valuable assets in the portfolios. Thereupon, the research conducted on cryptocurrencies can warn the crypto-investors about such biases in advance. However, given that data related to cryptocurrencies is confidential and API's received from exchanges that display transaction and price specific data is hard to be found in a desirable context, it is preferred to conduct the descriptive analysis on cryptocurrencies and to provide information about biases that have been observed among index investors. Three biases mentioned above are the mostly observed biases among stock investors and they can be tested by using quantitative data since qualitative data collected for cryptocurrency investors are not reliable because of its anonymity and difficulty of its tracking. Consequently, this research will play a pioneering role for further researches to examine and test variety of the cognitive biases among cryptocurrency investors.

To summarize, the thesis is structured as follows: first, the issue will be contextualized by explaining cryptocurrency market and its evolution in the literature. Secondly, clarification of the concept of rationality and whether investors act rational will be provided. The concept and importance of the normal distribution will be explained in detail. In the third section, there will be literature review of 3 cognitive biases and the methodology used for testing them in stock markets. At the fourth and fifth sections, the data and the methodology utilized will be illustrated. In the last section, a conclusion will be provided.

2. LITERATURE REVIEW

2.1 CRYPTOCURRENCY

Cryptocurrencies or "cryptocoins" are the investment instruments that have rapidly gained the popularity. The market cap and the price of the cryptocurrencies have touched all-time highs which were almost several billions U.S. dollars each day. Financial organizations and institutions have already invested to build digital currency technologies. For instance, nowadays blockchain-based technology startups are counted in booming numbers. Because of these high involvement of cryptocurrencies in investment and business world, it is crucial to interpret the market dynamics of them. Meanwhile, it should be noted that as cryptocurrencies are becoming popular, their rise or increase has been interrupted by variety of occasions like crises. It includes the collapse of Mt. Gox which took place in 2014 and the 2016 hack of Ethereum.

One potential threat for cryptocurrencies is because of cryptocurrencies' speculative nature. Most of the investors of these assets trade since they anticipate relatively high rise in their value. Such kind of collective excitement indeed leads to some bubbles as in the case of Bitcoin and consequent market crashes. On the other hand, the design options of various online exchanges can also contribute to the crashes. For instance; available functionality, GUI which is graphical user interface or API which is application programming interface can be reasons of design related problems if any data or code is not collected in an accurate way leading to collective excitement and indeed they can trigger market crushes. According to Brown and Lampinen (2017), markets are made by human beings, they are not naturally formed phenomena, and so that the designed objective; therefore, crashes are inevitable to encounter.

Since the concept of cryptocurrencies is new and each day new information is released, it is hard to make rational decision and investors are inclined to make investments to these assets expecting high returns. However, authorities can also be a factor in the investment of these assets as in the case of Venezuela or big players can also make conspicuously large bets on the cryptocurrency. Another reason for these investments is the peer influence among small individual traders according to Bikhchandani and Sharma (2000), Hirshleifer et al. (2003) and Spyrou (2013). Since the nature of these assets is very speculative, peer influence plays particularly crucial role in cryptocurrency ecosystem. Most of the trading is expected to be speculative as long as there is a general increase in the intrinsic value of the cryptocurrencies. Because of this uncertainty, most of the investors who have observed the chance of getting huge profit in the case of Bitcoin, are more likely to hope for the “next Bitcoin”. That’s why, each new altcoin is very appealing for them.

Cryptocurrency markets are the source of an investment platform that offers low transaction fee along with free and accessible public APIs as well as low minimum orders. Consequently, cryptocurrencies which are a novel type of virtual money or asset which depend on the distributed cryptographic protocols or distributed ledger, albeit the physical material or a centralized authority, in order to operate as a currency. Bitcoin was not the first cryptocurrency, however, it gained immense popularity and indeed it plays an indicator role. However, there are hundreds of altcoins or alternative cryptocurrencies even though most of them represent only a minor change to the code source of Bitcoin. In the case of Auroracoin, a trivial technical modification was made to LTC, but it was branded as an official cryptocurrency of Iceland. Auroracoin even had 500 million USD market cap at one point. Nonetheless, some other coins are coded based on real technical innovations. For instance, Ether is utilized by the Ethereum protocol for implementing fully functional globally distributed computer.

The main objects of this thesis will be Bitcoin (BTC), Ethereum (ETH), Litecoin (LTC) and Ripple (XPR) because of their high attractiveness to the investors and their engagement with some official government authorities.

BTC is released on January 9th in 2009 by Satoshi Nakamoto and it is a medium of electronic money. BTC is a decentralized virtual money that means there is no central bank or single administrator who can settle the transactions. Each transaction is executed with the peer-to-peer base within bitcoin network and there is no need for any intermediaries. Since it is a long ledger of each transaction and within anonymity context, which means all personal information is confidential, every single transaction information is confirmed and can be monitored by the whole network.

Ethereum is an open-source, publicly available and blockchain-based distributed platform which is created by Vitalik Buterin, Gavin Wood and Joseph Lubin in July 30th in 2015 and it has an operating system that features the smart contract functionality. Furthermore, it reinforces an altered form of Nakamoto consent through transaction-based state transitions. Plus, Ether is the token that its blockchain is created by the Ethereum platform.

Litecoin (LTC or Ł) is another peer-to-peer cryptocurrency almost identical to BTC and it is a software project that is released under MIT/X11 license and its source is open. Litecoin was released on October 7, 2011 by Charlie Lee on GitHub. Coins are created and transferred according to an open source cryptographic protocol which means again there is no central authority.

Ripple, released in 2012, is a gross settlement system which work in real time, the currency exchange and the remittance network which has been created by Ripple Labs Inc., technology company based in the US. Ripple is inclined to enable "the secure, instantly and nearly free global financial transactions for any size and with no chargebacks." Also, the ledger engages the decentralized native cryptocurrency which is known as XRP and it has been the 2nd largest coin due to its market capitalization.

2.2 NORMAL DISTRIBUTION

Inspired by the Central Limit Theorem, the normal distribution is considerably widespread distribution format that is utilized in technical stock market analysis along with various statistical analyses. The mean and the standard deviation are two parameters of the standard normal distribution. In normal distribution, it is expected that 68 percent of the observations are exhibited within one standard deviation of the mean and 95 percent are observed within two standard deviations and most of them or 99.7 percent are monitored within three standard deviations. However, it should be noted that even though all symmetrical distributions are normally distributed, the normal distribution is not always symmetrically distributed. Symmetrical distribution is the distribution type that one diving line can divide the observation histogram into two mirror images. Nevertheless, for normal distribution, actual data can be in the form of bell curve as well as the actual data can be 2 humps or series of hills.

The other two main components of the normal distribution are skewness and kurtosis that illustrates the fact that how different is the distribution from normal distribution. To be much more precise, skewness measures the distribution’s symmetry and since normal distribution is accepted to be symmetric, its skewness is expected to be equal to zero. If skewness of the distribution is less than zero, then it is stated that the distribution’s left tail is longer than the right tail. For positive skewness, it is expected that the right tail of the distribution is longer than the left tail. On the other hand, in normality check, skewness less or greater than absolute value of 1, shows the distribution is highly skewed. The table is moderately skewed in the case that the skewness is calculated between -1 and -0.5 or between 0.5 and 1. However, if it is between -0.5 and 0.5, then it can be concluded that the distribution is almost symmetric. Overall, it is a measure of the asymmetry of the probability distribution of the random variable around its mean.

The kurtosis statistic shows the height and sharpness of the central peak and measures the thickness distribution’s tail ends compared to a standard bell curve. If the distribution has large kurtosis, which can be explained as having observations in the fifth standard deviation of the mean, then the tail is extreme. Generally, the normal distribution does not have fat or thin tails and it has 3 kurtosis measure. Thus, having kurtosis lover than -3 or higher than 3 means distribution has heavy tails. Therefore, if a kurtosis of an observed distribution is greater than three, then the distribution has heavy tails compared to the normal distribution. If the kurtosis of the distribution is less than three, then it has thin tails compared to the normal distribution. Three is a measure of kurtosis that is used as a benchmark of normal distribution. It implies the distribution’s tails are not fat or thin.

The stock returns and prices have relatively different distribution. Since stock prices are bounded by zero and they can be increasing and reaching to any number unlimitedly, its distribution is not normal, but generally lognormal and have grater thickness in the tails. However, stock returns in real life is assumed to be normal even though kurtosis can be higher or lower than the absolute value of 3.

There are seven features of the normal distribution:

i. Normal distribution is symmetric around its mean.
ii. The mean, median, and mode are equal.
iii. The normal curve area is equal to 1.0.
iv. Normal distribution is relatively dense in the center (meaning most of the data is around the mean) and less dense in the tails.
v. Two parameters of the normal distribution are the mean (μ) and the standard deviation (σ).
vi. 68 percent of the observed data is within 1 standard deviation of the mean.
vii. Approximately 95 percent of observations are within 2 standard deviations of the mean.

However, lognormal distribution is utilized to illustrate stock or share prices and it has again the same 2 parameters of the mean and the standard deviation like in normal distribution. Nonetheless, since prices cannot be negative lognormal distribution is more felicitous for asset price distribution despite the fact that continuously compounding returns follow the normal distribution. One of the main characteristics of the lognormal distribution is that it is skewed to the right and has long right tail.

In summary, in most of financial models are based on the assumption that investors act rationally. To explain the mentioned rationality, the price distribution should be normally distributed and 68 percent of the price variations should be around mean and 1 standard deviation. However, as mentioned above, in the case of stock, index prices the rational decision making is not observed and there is irrational decision making which can be explained by some anomalies and cognitive biases according to behavioral finance and thus, traditional finance theories are not on the base of accurate assumptions. In this thesis research, I aim to show such irrationality in indexes and some cryptocurrency price distribution so that biases observed among stock investors can be adopted to the cryptocurrency investors.

3. COGNITIVE BIASES OBSERVED AMONG STOCK INVESTORS

The cognitive biases illustrated in this section are selected according to considerably meticulous research. Because generally those anomalies are tested according to qualitative data, it is hard to track the cryptocurrency investors and accuracy of their testimony. Therefore, biases that can be tested on not qualitative albeit quantitative data is preferable to avoid any misconceptions. The formalization of data in Java and Spring Data programs is a difficult procedure given time constraint. At least; the quantitative data can be found from sundry exchanges at a form of APIs. Needless to say, the biases mentioned below are the most commonly observed biases among stock investors and thereupon, any observed positive correlation between the index and cryptocurrency prices implies that one bias viable in one market can be provided as an instance for the other, as well. Furthermore, when concept of these biases are examined, it is the reason for such biases can be observed among crypto-investors.

3.1 REPRESENTATIVENESS HEURISTICS RELEVANT LITERATURE

3.1.1 Representativeness Heuristics

The Representativeness heuristic is a cognitive bias that demonstrates the level of similarity in features of two different samples. Typical labels are foundation to this anomaly. Tversky and Kahneman (1971) shows that people anticipate the concept of a chance wrong. To be much more precise, since people do not have access to all information available, generally they tend to take small samples from population as a representative and they make decisions according to randomly selected samples. Thus, this bias has significant influence on people's expectations according to Tekce (2016).

Boussaidi (2012) and Grether (1992) define heuristics as "a rule of thumb as well as guidance for decision making". The general consensus is that heuristics is one of the cardinal factors that affect human judgements and leads people to mistaken decisions. On the other hand, compared to other heuristics, representativeness heuristics is accepted to be the most vital heuristics that is the reason for stock price anomalies and irrational investor decisions according to Barberis, Shleifer and Vishny (1998) and according to Shefrin, (2008). Furthermore, according to Kahneman and Tversky (1972), when people find themselves in a situation that they do not know what to do, they make decisions about probabilities either according to previous similarities with a sample from population or development of the creation they have observed in some other samples. This is what they call as representativeness heuristics. Boussaidi (2012) also mentions that investors illustrate representativeness heuristics in their behavior when they take previous years' performance as an indicator for future performance and they do trading transactions based on this limited knowledge. Even though past performance of the company is not a good measure of future performance, investors assume the previous results to be similar to future earnings. In other words, without taking current economic conditions, companies' new investments so on into consideration, an investor can suppose the stock of a specific company to be meaningless to buy because of losses observed previous years' income statement.

Investers' various reactions to specific stocks were firstly analyzed by Barberis, Shleifer and Vishny (1998). Their model show that investors mistakenly assume that earnings follow either the mean reversion or trend not a random walk. To clarify, if the investor gets a negative announcement, he does not react to this announcement in a timely fashion since he believes mean reversion will be observed and announcement will be observed gradually. However, if he has heard such announcement before and has information how that announcement affected the market, without analyzing the conditions meticulously, he tends to overreact to the announcement and estimate future prices or returns according to his previous limited knowledge.

The effect of representativeness heuristics has not been analyzed well. Therefore, some experts find representativeness heuristics not felicitous to evaluate behavior of individuals in current economical conditions. ((Charness, Karni and Levin 2010), (Grether 1980), (Grether 1992)). On the contrary, other relevant studies with behavioral finance aspect have found that representativeness heuristic impacts an investor's decision in assessing stocks ((Alwathainani 2012), (Kaestner 2006), (Frieder 2004), (Frieder 2008), (Barberis, Bloomfield and Hales 2002), (Shleifer and Vishny 1998)).

Kahneman and Tversky (1971, 1972, 1974, 1982a, 1982b) state that people illustrate representativeness heuristics in various aspects of their everyday lives. To clarify, people tend to use limited knowledge about provided example as a representative when they face with unknown situations they find themselves in uncertainty. They make decisions irrationally and they do not consider probabilities of possible outcomes.

Tversky and Kahneman (1974) on the other hand, show that estimations about future stock prices can be explained by this bias. To be much more precise, people illustrate extrapolation bias which is another form of representativeness heuristics while purchasing specific stock. This means that investors are more likely to buy stocks that have upward trend line. rend lines (Andreassen and Kraus 1990). In other words, if prices of a specific stock follow 2 bull period, then investors are more likely to purchase that stock while relevant bear period is a signal for selling that stock. This decision is made irrationally according to extrapolation bias which states that people extrapolate recent past prices. DeBondt (1993) also shows past returns are also accepted as a representative of expected stock prices.

Dhar & Kumar (2001) on the other hand, shows that in not only past prices or past returns play representative role for investors, but also some investors take abnormal returns into consideration while making estimations about future prices. Therefore, some other variables can be taken as a representative.

Findings presented by Grether (1980) confirm representativeness heuristic for novice or financially unmotivated subjects; the evidence is less clear for other subjects. Chen et al. (2007) ascertains that representativeness heuristic is only valid to individual investors. Institutional investors are not as affected as individual investors from recent past return performance. Hence it can be hypothesized that sophisticated investors are less inclined to representativeness heuristic. According to past price to earnings ratio, stocks can be classified in two categories: value and growth stocks. Lakonishok et al. (1994) state that investors assume past high price to earnings ratio of growth stocks. However, since value stocks have relatively lower price to earnings ratio, they bear more risk compared to growth stocks. More risk means probability of more return. Therefore, in the long run, value stocks can outperform growth stocks. Nevertheless, according to past return performance, investors make irrational or biased decisions while purchasing growth stocks. Needless to say, some investors see short term movements as a representative for long term expectations which is another form of representativeness heuristics (Barberis et al. 1998).

Benartzi (2001) has conducted a research on S&P 500 firms' retirement saving plans. He also finds positive relationship betwixt past returns and employees' future estimations. They illustrated extrapolation bias while decision making process and making judgements about their retirement plans.

3.1.2 Representativeness Heuristics Testing

Gongmmeng et al. (2007) states that investors purchase stocks according their past recent returns or past positive abnormal returns since they assume these stocks will do better in the future. Abnormal returns are equal to a difference between an actual return and the market return. In comparison to other published studies, Jegadeesh and Titman's (1993, 2001) show investors buy past or recent winners and sell past or recent losers. This is trading strategy of most of the investors. They tend to take last three to twelve months' return into consideration for calculating abnormal returns. Indeed, this is another version of momentum effect. Therefore, it can be concluded that momentum effect that is also found in European countries (Rouwenhorst (1998) is another form of representative that people use in their judgements about future.

Some people use reverse of extrapolation bias while their decision making process. To be much more clear, they demonstrate gambler's fallacy in their behavior. They assume that trend is broken and reverse of the current situation is expected. Thus, they use past returns or prices as an indication of reverse action and make judgements based on representativeness heuristics that is very different than extrapolation effect (Shefrin 2005).
Chan et al. (2004) argues that the correlation between recent price sets of stocks and buy orders is the best way to calculate representativeness heuristic. Furthermore, Chen et al.

(2007) and Barber et al. (2009) also used past stock price direction and its relationship with investors' purchase decisions as a measure of representativeness heuristic.

Chen et al. (2007) use buy and sell transactions to check if representativeness heuristic exists among Chinese investors. According to extrapolation principle, investors tend to buy stocks that have upward trend in the last four months. However, the authors observe the fact that these investors missed the fact that almost all of the stocks had positive performance during the last four months have almost normal return in a long run. Moreover, Barber et al. (2009) shows similar results and use extrapolation as a determinant of representativeness heuristic. They find that investors purchase stocks that have strong returns in recent past. This observation also demonstrate that such correlation is observed mostly in a yearly base and lasts maximum of three years. Thus, it can be concluded that representativeness bias reaches its zenith for four months and a yearly returns, however, diminishes for longer term return results. Therefore, in order to calculate representativeness bias, short period of time should be taken into consideration.

Bildik and Gülay (2007), calculated positive returns for each purchase transaction by dividing number amount of positive returns observed in the last nighty days of trading to nighty. Therefore, they used average positive return of all buy orders as measure of representatiteveness heuristic. Same methodology is valid for thirty and a hundred fifty trading days as well.

Tekce (2016) on the other hand, analyzes the factors that has an impact on representativeness heuristics. He calculates and finds that age has significant influence on representativeness. Also, gender of the investors is also crucial factor as female investors illustrate representativeness heuristic more compared to male investors. How experienced the investors is another factor impacts representativeness heuristic. There is negative relationship between experience and representativeness heuristic. As long as portfolio value of the investor is low, they are more likely to exhibit representativeness heuristic. In the case of Turkish investors, people living in Marmara region tend to exhibit higher representativeness heuristic compared to people living in Southeast Anatolia region.

Consequently, the main way to analyze representativeness heuristic is calculating positive return trend. Nonetheless, in the case of not being able to obtain data about investors' transactions, the prices can assist observing this bias. Since it has been mentioned that representativeness heuristic can be seen when investors tend to buy increasing instruments, illustration of the relationship between volume and prices can be one way of observing it. To be much more precise, if price of specific cryptocurrency is increasing then it must be confirmed with higher volume to support representativeness heuristic.

3.2 OVERCONFIDENCE RELEVANT LITERATURE

3.2.1 Overconfidence

Overconfidence is the unjustified confidence in one's decisions and aptitudes. Odean and Barber (1999) state that people are overestimating their capabilities, knowledge and expectations. Daniel et al. (1998) define an overconfident investor as one who overrates the accuracy of her private information wave, but not of information waves publicly available for all. Odean (1998a) posits the fact that overconfidence is the certainty that a trader assumes she has the knowledge or information that is more accurate than essentially it is. In his research, Odean (1998b) demonstrates that overconfident investors have lower expected returns because she trades more frequently than any rational trader. Having considerable overconfidence is the indication of larger amount of trading leading to lower expected utility. Odean (1998a) describes overconfidence as the belief that a trader's information is more precise than it actually is. Besides, overconfidence leads to an increase in trading activity since investors feel too certain on their decisions about shares or other financial instruments and they tend not to consider others' opinions enough. Harris and Raviv (1993) and Varian (1989) conclude this action as investors' heterogeneous beliefs. Odean and Barber (1999) state that according to overconfident investors the decisions they have made bears less risk.

Gongmmeng et al. state that overconfident investors think all positive returns or increased portfolio value is because of their ability. They extrapolate their idea by stating that overconfident investors are thinking to use their exceptional capabilities in order to get excessive returns. Hence, trade frequency of such investors are higher compared to rational investors and they generally undervalue risks related with frequent trade actions ((Kyle & Wang 1997) and (Odean 1998b)).

Analysis of the subjective probabilities' calibration have demonstrated that generally people are prone to overrate their capacity and their knowledge according to Alpert and Raiffa (1982); Fischhoff, Slovic, and Lichtenstein (1977). That kind of overconfidence was monitored among several professional specialists including psychologists working in clinics according to Oskamp (1965); among physicians and nurses according to Christensen-Szalanski and Bushyhead (1981) and Baumann, Deber, and Thompson (1991); among investment bankers according to Staël von Holstein (1972); among engineers according to Kidd (1970); among entrepreneurs according to Cooper, Woo, and Dunkelberg (1988); among lawyers according to Wagenaar and Keren (1986); among negotiators according to Neale and Bazerman (1990); and among managers according to Russo and Schoemaker (1992).

People are, in fact, unrealistically positive about future occasions. People indeed anticipate positive things will more often happen to them when compared by their friends or peers according to Weinstein (1980). The same idea is analyzed and proved by Kunda in 1987, too. Marks (1951), Irwin (1953) and Langer and Roth (1975) claim that people also illustrate whimsically positive viewpoint towards haphazard events.

Also, people make highly optimistic self-assessments according to Greenwald (1980). Majority of people assume themselves to be more capable than a normal average person according to Taylor and Brown (1988). Needless to say, human being has a tendency to overrate her inputs to past progressive results. Human being is more inclined to remember their accomplishments rather than disappointments. To clarify, Fischhoff stated people mis-remind of their own forecasts so as to overstate in reflection what they actually knew in forethought" (1982, p. 341).

Taylor and Brown (1988) has found that overstated beliefs in somebody's capabilities and unrealistic positivism can be a reason for higher motivation, more perseverance, considerably efficient performance and eventually, more success (p. 199). According to Odean and Barber (1999), these believes can also lead to biased judgments. Thus, over specified time period, these traders assume the stocks they have bought will outperform the stocks they have sold. Plus, they assume the costs related to all transaction procedures will be covered by the difference earned by purchase and sale actions. If, however, speculative traders are informed, but overestimate the precision of their information (one form of overconfidence), the securities they buy may outperform those they sell but possibly not enough to cover trading costs. What's more, Poyser (2018) illustrates the overconfidence as the intensified credence on her own capacity, knowledge, and abilities which is intrinsically related with optimism. Furthermore, he defines this idea with the concept of self-reliance about personal conclusions that entails notions including mis-calibration, over-precision and positivity, that actually are meanwhile connected with an overreaction to haphazard occasions according to findings of Barber and Odean (2013), Barberis and Thaler (2002) and Kahneman and Riepe (1998).

There are several reasons for overconfidence bias. According to Miller and Ross (1975) and Kunda (1987) there is self-attribution bias which means that successful results are because of our own skills; however, unsuccessful outcomes are because of bad fortune. Secondly, Langer (1975) explicates illusion of control as the propensity of human being to overrate her skills to have impact on occasions that she has no effect over it. People unrealistically assume future positive result of something and they believe in it naively ((Weinstein 1980), (Kunda (1987)). Russo and Shoemaker (1992) provide information about confirmation bias and explains how it can be interlinked with overconfidence.

Also, Svenson (1981), shows that overconfidence shows that people are more inclined to think that their capabilities are exceptional and better than an average person. Another determinant of overconfidence is calibration. It can be clarified as the fact that people they to believe their estimations are always true. Deaves et al. (2010) show that a mis-calibrated agent thinks she makes lower amount of mistakes than she makes.
Tekce (2016) states that investors make lossess during their decision making process since they overrate their skills and they anticipate the returns they will earn will be higher if they trade more. They also do not consider trading costs.

Studies of Fischhoff et al. (1977), Russo and Shoemaker (1992), Griffin and Tversky (1992), Kahneman and Riepe (1998) illustrate the fact that one of the widespread biases among invetors is overconfidence. Odean (1998) also made research on investment bankers and executives of companies and observed overconfidence. He concludes that overconfidence leads to higher expected volume, market depth; however, it has negative influence on expected utility of investors.

Similar to findings of Barber and Odean (1999), Barber and Odean (2001), Chen et al. (2007), Acker and Duck (2008), Graham et al. (2009), Grinblatt and Keloharju (2009), Hoffmann et al. (2010), Tekce (2016) also found that male Turkish stock traders exhibit more overconfidence than female traders. On the other hand, Chen et al. (2007) concluded that there is influence of nationality in overconfidence and Chinese investors exhibit more overconfidence than US investors. Similarly, Tekce (2016) also hypothesized and illustrated that Turkish investors trade more frequently than US traders.

Unlike findings of Tekce (2016), Graham et al. (2009) displayed the influence of wealth and education is positive on overconfidence since those investors assume themselves to be much more proficient. Hence, they assume they have the most accurate information and they are able to make the most accurate decisions. However, similar to research of Tekce (2016), Ekholm and Pasternack (2007) also found that investors whose portfolio is small, are more overconfident. Education level decreases the biased decision making.

3.2.2 Overconfidence Testing

De Bondt and Thaler (1985) see overconfidence as the chief factor that determines trading conundrum in terms of behavioral finance. According to Kyle and Wang (1997), overconfident investors assume they have better knowledge about financial instruments and as it is supported by Benos (1998), they trade aggressively. Therefore, how frequent the trading action is is taken into consideration as a benchmark value to indicate overconfidence among investors. ((Barber and Odean 2000), (Barber and Odean 2001) and Odean 1999)). However, this measure is highly volatile and cannot be accepted as a solid proxy. Gongmmeng et al. (2007) state that overestimate their ability and they assume they have excellent ability to trade and they can reach the best available information sources. Therefore, they are more likely to trade more even aggressively. However, the number of investors who truly have exceptional trading skills are very few. Therefore, overconfident investors just overestimate their capabilities. To conclude, frequency of trading is accepted to be one of the tools to show misbehavior of overconfident investors.

To test overconfidence in the accuracy of information, Barber and Odean in 1999 conducted a research to determine if the securities purchased by the investors outperformed the securities that they sold. They wanted to ascertain if gain was adequate to afford costs related to commission fee etc. Also, they examined that if trading costs are taken as zero, what is the relationship between securities bought and sold. They wanted to see whether investors had better or worse performance. In their research, transaction data were collected for eighty-four, two hundred fifty-two and five hundred four days.

In their sample data, average commission was same for purchase and sale actions and equal to purchase price's 2.23 percent. Meanwhile, 2.76 percent of sale price was charged as commission fee. The average commission was calculated to be 2.76 percent of the sale price. Hence, in the case that somebody sells a security, then that person uses that sale proceeds to purchase new security, then almost 5 percent is expected to be total amount of commission fee. They also calculated that the average bid–ask price spread was 0.94 percent. Thus, the average total cost for the round-trip trade is calculated to be about 5.9 percent. In summary, an investor who sells several securities and purchases other securities because he assumes the securities that he is buying will outperform the ones that he sold. On average and when you trade equally, the return should be 6 percent higher on a security to cover all trading costs. The second hypothesis of the author assumed the same time horizons but ignoring trading costs and stated that generally the average return of purchased securities was less compared to sold securitites. Consequently, for all time horizons, the market-adjusted return of stocks purchased was less than the return of sold stocks. The stocks that investors bought underperformed the stocks that they sold. They proved this hypothesis to be true not only for market-adjusted returns but also actual returns. Barber and Odean (1999) concluded that overconfident investors do not make profit as they pay commissions and their gain does not cover their loss. Also, most of the time the stocks they purchase do not out-perform the stock that they sell. However, authors also look for other possible explanations to excessive trading. For instance, investor can be in a shortage of cash or she can face tax losses. Also, willingness to have a portfolio bearing less risk can be another reason.

On the other hand, Gongmmeng et al. (2007) took sample data of 75,000 investors (trading activities: stocks bought and sold) from anonymous brokerage house for time period of 1998-2002. They also used Odean's (1999) methodology and calculated an average subsequent stock returns which investors trade. Specifically, they calculated the total stock return during 84 trading days which is equal to 4 months, 252 days equal to a year and 504 days which is equal to two years. They concluded that there is difference in decision making process of institutional investors and institutional investors in China have better trading decisions compared to individuals.

As mentioned above, overconfident investors have higher turnover ratio. According to analysis conducted by Barber and Odean (1999, 2000, 2001 and 2002) turnover ratio of overconfident investors is high. What's more, amount of transactions is more according to Hirshleifer and Luo (2001), Chuang and Lee (2006) and Hoffmann et al. (2010). In other words, Glaser and Weber (2007, 2009) and Graham et al. (2009) explicitly show that portfolio of overconfident invetors change more frequently. Moreover, Gervais and Odean (2001), Statman et al. (2006), Grinblatt and Keloharju (2009) state the fact most of the daily trade actions are executed by investors who exercise overconfdence in their behaviour. According to Barber and Odean (2001) summation of one-half monthly sales and purchase turnovers is equal to monthly portfolio turnover. In order to calculate monthly sales turnover he multiplied is month t's sold shares with price taken at the beginning of the month. Later he divided this value by household's portfolio's market value at the total beginning of month t. On the other hand, in order to calculate the monthly purchase turnover he multiplied previous month's purchased shares with that month's beginning price. Then he divided that amount by market value of that month's household's portfolio. For calculating annual or yearly turnover, he multilied monthly turnover with 12. In his research, Tekce (2016) used buy and sell transactions of stock investors in a month. Also, he took general portfolio position of all Turkish investors, which included stocks, funds, private sector bonds, warrants etc. He also used turnover method for overconfidence analysis.

Josephs et al. (1992) shows positive correlation between self-esteem and risk taking. They claim that people who are willing to take more risk are the individuals with high self-esteem. Needless to say, Campbell (1990) displays that individuals with high self-esteem are the ones with high self-confidence. Thus, it can be concluded that overconfident investors are more prone to take more risk. Also, another study shows that riskier securities are traded by overconfident investors. (Chuang and Lee 2006). The riskiness of the security is calculated with return volatility which is shown as variance and firm specific risk which is non-systematic or residual risk. Glaser and Weber (2009) also claim that overconfident investors purchase stocks with high risk. That is, portfolio riskiness can be a good indicator of overconfidence measurements. Therefore, without available return data just by checking risk levels of investors' portfolios we can have insight about their overconfidence level. For instance, this approach can be simplified according to market capitalization and coins which have high mcap can be accepted as less risky and evaluation can be based on this assumption.

In conclusion, Heath and Tversky (1991) uses competence hypothesis in their study. They posit the fact that overconfident investors do not diversify their portfolios a lot and mainly focus on companies that they are familiar with. Therefore, the amount of investment is limited with small numbers of companies. Odean (1998) also finds that portfolio of overconfident traders is not well-diversified. On the other hand, Goetzmann and Kumar (2008) illustrates high portfolio turnover as a sign of overconfidence. Also it is an indicator of under-diversification. According to literature, using average amount of stocks in the portfolio is not vigorous way to measure diversification level.

3.3 ANCHORING RELEVANT LITERATURE

3.3.1 Anchoring

While making judgments about variety of topics, people are inclined to make decisions according to the information or value that is available to them. This is valid although that number or value is a random value. This is known as an anchoring bias or anchoring. (Kudryavtsey and Cohen 2010). Anchoring is a cognitive type of bias that displays the situation where people make decisions on their initial impression. In the case of investments, they tend to make estimations about returns based on quantitatively available values. Despite the fact that the available value is irrelevant to the matter, people tend to make estimations closer that available value which is anchor. (Kahneman 2012, p.119).

Trofimovich and McDonough (2011) describe anchoring as a priming effect. To be much more precise, a "phenomenon in which prior exposure to specific language forms or meanings either facilitates or interferes with a speaker's subsequent language comprehension or production" is priming effect. Additionally, even though Kahneman did not agree in all aspects of his partners' viewpoint, he accepted the real existence of anchoring and he insisted in his claim that the priming effect is the cardinal influence in this bias. In fact, the number provided serves as a suggestion role. Mind produces decisions without time lag. Lam (2018) argues that anchoring is intuitive process that mind makes judgements and computations straightforwardly.

Kudryavtsey and Cohen (2010) denote that as long as knowledge about the phenomenon is limited, people are prone to be influenced by even random, haphazard anchors while making assumptions about object's characteristics or predicting its related future outcomes. Thus the potential for manipulations gets wider from the angle of those who are interested while convincing people to make an investment in a stock or to purchase a product.

Kahneman et al. (1982) states that human make judgments or decisions deviating from rationality. In their research, Tversky and Kahneman (1974) suggest that while assessing the probability of uncertain events or forecasting or prompting certain values or consequences, people mainly depend on a variety of simplifying procedures of decision-making, and this is called heuristics. One of the heuristics that is discussed in the process is anchoring (or anchoring bias). They argue that in many situations people make estimates by considering an initial value that they adjust upwards or downwards to yield a final estimate. Such adjustments are often insufficient, leaving judgments biased in the direction of the initial "anchor" value.

Some research conducted in past show two approaches: 1 Standard anchoring: There is direct contrast between an anchor value and objective (It has been illustrated in the works of Chapman and Johnson (1994) and Tversky and Kahneman (1974), 2. Basic anchoring: There is no direct relationship between an anchor and objective. Wilson et al. (1996) have conducted an experiment on students who suffer from cancer. The students who suffer from cancer preferred to write five pages of big numbers instead of words. Some other researches including Northcraft and Neale (1987) and English and Mussweiler (2001) have also provided several crucial "starting or beginning points" such as listing price or sentence demanded so on. Subsequently, they have asked for the target estimations, without any comparison with the anchors however, they have played the role of anchor.

To show the magnitude of this effect, Tversky and Kahneman (1974) have implemented a research and asked to their participants whether they can assume or say the percentage of African nations in the United Nations and they actually provided the target number so that participant can make estimations which are lower or higher than the provided target number which is actually an anchor. Indeed, that target number or anchor was haphazardly determined. It was an arbitrary number found by just spinning the wheel of fortune (e.g., sixty-five percent or ten percent).

Anchoring effect has been proven to be an accurately universal occurrence and it is observed in each aspect of everyday life. It can be seen in the works of Mussweiler and Strack (1999a) and English (2008). On the other hand, Jacowitz and Kahneman (1995) have asked various questions like height of Everest. Their report states that students' estimations were based on the anchor values provided to them. To clarify, if higher anchor values were given to students, then they tend to say values for questions asked. ((Strack and Mussweiler 1997) and (Mussweiler and Strack 1999b)).

Cervone and Peake (1986) have documented that people who get higher value anchors consequently have higher estimations about their own capabilities than people who have been provided relatively lower anchor values. The anchoring bias has crucial impact on people's probability evaluations according to Plous (1989). Additionally, Chapman and Johnson (1994) have asked sample of people to assess lottery numbers that has various expected prices as well as their amounts, and have found that if the given anchor value was higher, then the minimal sum amount they could have sold the lottery was higher.

English and Mussweiler (2001), in the same spirit, have carried an experiment which included a group of professional judges and they have concluded which the decisions about sentencing have been anchored according to the sentence anchors demanded by prosecutors. The magnitude of this influence proves to be intense, as judges who consider a higher demand of 34 months ask for final sentences (for the same crimes) which are almost 8 months longer than the judges who think lower demand of around 12 months. This effect is observed as to be autonomous judges' experience.

English (2008), on the other hand, has asked a number of students to make estimations about the average price of a German midsize car, and then he provided students both a standard anchoring and additional information. He has found that students’ estimations are biased and anchor values play crucial role in providing estimations.
Anchoring effect is autonomous for many moderating variables. Also, anchoring effect exists in almost all cases even when anchor values are lucidly vague for the analytical estimations. ((Mussweiler and Strack 2000), (Tversky and Kahneman 1974)). Besides, the anchoring phenomenon is not influenced by the extreme value of an anchor according to Chapman and Johnson (1994) and Strack and Mussweiler (1997). Therefore, inconceivably extreme values yield an effect.

Gruen and Gizycki (1993) explained that forward discounts cannot solely explicate subsequent exchange rate movements. In fact, anchoring is used to explain these anomalies. The phenomenon of the anchoring can also be relevant to the "sticky prices" which are discussed by macroeconomists. Therefore, past prices are generally and mainly taken as signals of the new prices. The new prices generally are prone to be as close as possible to the past prices. If the value of the commodity is ambiguous, then anchor value is the most crucial determinant of the new prices.

Zielonka (2004) has carried an experiment which also involved financial analysts. He found that in technical analysis some variables are accepted as mental anchor including specific historical peaks or lows. Simonson and Drolet (2004) also have reported that consumers accept some values as an anchor while paying or accepting. To be much more precise, willingness-to pay or willingness-to accept are determined by some anchor values. Mussweiler and Strack (2000) posits the fact that assimilation of the anchor into estimations is mainly related with information about the subject.

Baker and Wurgler (2006) state that if investors have less information about the stocks or if the stocks have lower capitalization or growth and if they are highly volatile, then investors more sensitive to sentiments.
Kudryavtsey and Cohen (2010) state that when an investor decides to purchase a stock or tends to estimate its future returns, she does not mainly consider the company itself, but anchors. Therefore, anchoring bias seems to have its strongest effect when we have no real idea of what the right decision is. Tokarchuk (2017) gives an example of novice investors within the context of cryptocurrency since it can be something abstract with unpredictable behavior.

3.3.2 Anchoring Testing

Lam (2018) used a set of APIs that was provided by Kraken exchange. The author took bids and asks data of Bitcoin from 25 November 2017 till 03 March 2018. Records included 30-minutes intervals. Moreover, Bitcoin market prices were attained with the API. Bids and asks data compromise the placing the order date, quantity and offered price. Price data illustrates daily BTC open, high, low, close, average prices. To examine the bitcoin prices and investors’ orders time series analysis as well as correlation used.

A sequence of random variables indexed by time is called stochastic process or a time series process (Wooldridge, 2013, p.345). The formula below displays the static model.

$$Y_t = ß_0 + ß_1 z_1 + u_1 = 1,2, \ldots, n \quad \textbf{(3.1)}$$

Nonetheless, if more variables affect dependent variable with a time lag, then formula 3.2 is used (Wooldridge 2013, p. 347). This indicates a finite distributed order q's lag model.

$$Y_t = a_0 + \partial_0 z_t + \partial_1 z_t\text{-}1 + \ldots + \partial_q z_{t-q} + u_t \quad \textbf{(3.2)}$$

According to above formula, the relationship betwixt order price and market price is analyzed with 10 days of lag. This is similar to the method used by Liao, Chou and Chiu (2013). This investigates a relationship betwixt order price changes (OrdP) and market price changes (MarP) in relation to observed anchoring bias.

$$\text{Ord } P_t = a_0 + af_0 \text{ MarP}_t + af_1 \text{ MarP}_{t-1} + \ldots + af_{30} \text{ MarP}_{t-10} + u_t \quad \textbf{(3.3)}$$

On the other hand, Lam (2018) wanted to see whether, there is difference in the effect on Bid and Ask prices to provide an extra profound information.

Time series face stationarity problem. A stationary time series has not stable probability distribution. It means if sequence's random variables shifted ahead x time periods, then joint probability is unchanged (Wooldridge). If a time series does not fit into this criteria, then it is non-stationary and inaccurate forecasting can be made in analysis. Dickey-Fuller test (Dickey et al. 1976), Phillips-Perron test (Phillips et al. 1988) and KPSS test (Kwiatkowski et al. 1992) are unit root tests used to transformation of data from nn-stationary to stationary.

Firstly, BTC market prices', bid prices' as well as ask prices' raw data can be in order to simplify the analysis. Secondly, daily mean values log-transformed in order to normalize data, then first order differenced in order to remove data's non-stationarity nature.

Lam used all bids' raw price data from Kraken exchange. In this research, the raw dataset, some bid and ask orders were under or over Bitcoin's market price. The market price is the average price of all price fluctuations in a daily base. Thereupon, several bid orders could follow daily high price or several ask orders could follow daily low price. Author checked Market_Price, Order_Price, Bid_Price and Ask_Price datas' stationary status. Thus, data has been normalized.

Using the new transformed dataset, regression analysis betwixt the order price (OrdP) changes and market price (MarP) changes is conducted. According to the analysis, if past day's market price rises 1 percent, then order prices rises about 0.954 percent. Lam (2018) concluded that there is a strong correlation betwixt the order price changes and Bitcoin's market price changes. This implies an investor alter her order price according to market price change. Therefore, anchoring effect is observed in Bitcoin prices. Also, the market price influences bid orders more than ask orders. In Bull and Bear cases he was unable to find any difference observed. To sum up, regression analysis approach is the best way to test the anchoring effect.

4. DATA AND METHODOLOGY

4. 1 HYPOTHESES

H1: Both index prices (S&P500, Nasdaq, BIST100, BIST30) and cryptocurrency prices are not normally distributed.

Based on the previous analysis, stock prices are not normally distributed. Both index and cryptocurrency prices are expected to display the similar irrational decision making impact. Therefore, the indices and cryptocurrencies tested within a given time horizon are expected to display non-normal distribution. This can be proven by various normality check tests by utilizing SPSS. They are Kolmogorov-Smirnov and Shapiro-Wilk tests, Normal Q-Q and Detrended Q-Q Plot, histogram and box plot.

H2: There is a positive correlation between Bitcoin and other specified cryptocurrencies (ETH, LTC, XPR).

Since it is one of the firstly released coins, BTC plays a leading role for other coins. The huge price changes in BTC have affected the overall coin market's market cap; thus, the majority of the cryptocurrencies are sensitive to the changes in BTC prices. This phenomenon will be proved by running regression analysis.

H3: There is a positive correlation between index prices and BTC prices.

Since both illustrate highly volatile prices, it is expected to observe the same sensitivity towards market announcements. Therefore, this positive correlation can be tested by regression analysis by taking BTC as a dependent variable and index price samples as independent variables.

4.2 METHODOLOGY DEVELOPMENT

I aim to make this study as an exploratory research typology. This study will explore the relationship between 4 cryptocurrency market prices and order behaviors of investors for a new interpretation of the market. The nature of research can be summarized in two categories, quantitative and qualitative research. As Mark Saunders et al. (2009) described: quantitative method is used as a synonym that implies a data collection technique or data analysis procedure that generates or uses numerical data. The thesis is based on quantitative method and it is a descriptive analysis done by both SPSS and Excel Data analysis. It includes Normality check and Regression Analysis. Moreover, descriptive Statistics of the price data of each index and cryptocurrency is analyzed.

Quantitative data is used since market activities in cryptocurrencies are done in a digital world by anonymous users. This is one of the core values offered by cryptocurrency, maintaining secrecy of its users' identity.

Alan Bryman and Emma Bell (2011) defined structured observation as follows:

Structured observation is a quantitative method that concerns how frequent the actions of a subject (Saunders et al. 2009). It is called as systematic observation and helps researcher to employ the observation's formulated rules. These rules notify observers where to look for and what technique they need to utilize.

The plan is to adopt the observation research strategy by aggregating price data of both 4 indices and 4 cryptocurrencies from Bloomberg Platform. Owing to time constraint, this thesis mainly conducts descriptive analysis and aims to play an initial step role for further and direct examination of the biases among the illustrated cryptocurrencies. First, where the data is obtained from is clarified. For instance, in Turkey, there are several exchanges trading variety of cryptocurrencies; however, not all of them trades more than one cryptocurrency. For instance, sistemkoin.com is the 50th largest cryptocurrency exchange in the world and Turkey's largest cryptocurrency exchange where majority of cryptocurrencies are traded and 47 cryptocurrencies are traded in ovis.com.tr. On the other hand, btcturk.com trades BTC, ETH, LTC, TETHER and

XRP. koinim.com trades BTC, ETH, LTC, BCH, DOGECOİN DASH; koineks.com trades BTC, ETH, LTC, Dogecoin; digilira.com trades BTC, ETH, LTC and Zcash; piyasacoin.com trades just BTC and ETH and paribu.com only BTC.

However, given that Bloomberg Platform is the one of the most prominent data providers, the price data for both indices and cryptocurrencies have been derived from publicly available Bloomberg platform. Furthermore, the price data is collected for a 3-years period for all indices and for bitcoin from 26.04.2016 to 26.04.2019, but for a 1 year and 2 month period for ETH, LTC and XPR from 08.02.2018 to 26.04.2019 since Bloomberg provides data for those cryptocurrencies starting from that specified date. The daily last price is taken for testing. At the tables and figures, BTC prices are noted as XBTUSD BGN Curncy PX_LAST, ETH as XET BGN Curncy PX_LAST, LTC as XLCUSD BGN Curncy PX_LAST, XRP as XBT BGN Curncy PX_LAST, S&P500 as SPX Index PX_LAST, Nasdaq as NDX Index PX_LAST, BIST100 as XU100 Index PX_LAST, BIST30 as XU30 Index PX_LAST.

To do normality check, Kolmogorov-Smirnov (K-S) and Shapiro-Wilk tests are utilized. The data is analyzed both in Excel and in SPSS. Both tests are based on the Null Hypothesis which posits that the sample price data is normally distributed. The point is worth noting that the Kolmogorov-Smirnov is a nonparametric and Shapiro-Wilk is a parametric test. Though both tests can be used for normality check, it is advisable to use Kolmogorov-Smirnov test in the samples which has a size larger than 2,000. Since sample size used in this study is smaller than 2,000, it is advantageous to utilize not Kolmogorov-Smirnov test rather Shapiro-Wilk test as it is applicable for sample size smaller than 2,000. In fact, Shapiro-Wilk test can be misleading for samples having relatively larger size due to its sensitivity to even very trivial deviations. Both methods have been utilized for double check. The main criteria for checking both tests is following: if the p value which is found is less than the alpha level which of 10 percent, 1 percent or 5 percent, then the Null hypothesis stating the sample is normally distributed can be rejected. It means that there is evidence that the data is not normally distributed. However, I did not merely rely on those tests and utilized also other sources including a Q-Q plot analysis, histogram check and box plot analysis by taking outliers into the consideration.

In the Kolmogorov-Smirnov (K-S) and Shapiro-Wilk test tables, D shows difference, df displays the degrees of freedom (equal to N) and p or sig. depicts the statistical significance. If “sig.” <0.05 (alpha=5 percent), then the Null hypothesis is rejected, which means the data is not normally distributed.

Plus, a Normal Q-Q or Quantile - Quantile Plot indicates the comparison of the observed quantiles data. Prices are shown as dots or circles. It is a graphical method to compare probability distributions by plotting the quantiles. If the points are closer to the linear line, then it can be concluded that the sample data is normally distributed.

On the other hand, Detrended Q-Q Plot illustrates a horizontal line. If the sample is normally distributed, then the quantiles should be at the origin. In fact, each point of circle shows the difference between the expected quantile and observed quantile. Any deviation from the horizontal line illustrates deviation from the normality.

Moreover, box plot provides information about outliers and about the location of the quartiles. By looking at the box plot, the height of the quartiles can be checked and the symmetry of the tails can be analyzed which provides the information about normality.

According to the histogram, distribution of the data can be visually seen and assessed. It is also used to compare the shape of the distribution and provides graphical view about the location, skewness and kurtosis of the distributions.

5. FINDING / DATA ANALYSIS

5.1 NORMALITY CHECK

5.1.1 Kolmogorov-Smirnov (K-S) and Shapiro-Wilk Tests

In order to test hypothesis 1, the data was taken from Bloomberg and SPSS was utilized to test the normality. Index prices and cryptocurrencies are tested separately. Descriptive variables and extreme values for all samples are calculated as it can be seen from the tables below:

Table 5.1: Descriptives (Indices)

			Statistic	Std. Error
SPX Index PX_LAST	Mean		10533,54059	126,0052527
	95% Confidence Interval for Mean	Lower Bound	10286,17671	
		Upper Bound	10780,90448	
	5% Trimmed Mean		10358,98400	
	Median		9622,162600	
	Variance		11955624,76	
	Std. Deviation		3457,690668	
	Minimum		5775,6114	
	Maximum		19771,0060	
	Range		13995,3946	
	Interquartile Range		4992,2610	
	Skewness		,660	,089
	Kurtosis		-,570	,178
	for Mean	Upper Bound	26487,12453	
	5% Trimmed Mean		25299,93758	
	Median		22772,24050	
	Variance		99201374,75	
	Std. Deviation		9959,988692	
	Minimum		12140,4426	
	Maximum		51854,0702	
	Range		39713,6276	
	Interquartile Range		15364,7742	
	Skewness		,626	,089
	Kurtosis		-,670	,178
	95% Confidence Interval for Mean	Lower Bound	94250,27653	
		Upper Bound	96066,66265	
	5% Trimmed Mean		95038,42558	
	Median		95368,59000	
	Variance		161159550,4	
	Std. Deviation		12694,86315	
	Minimum		71594,9800	
	Maximum		120845,3000	
	Range		49250,3200	
	Interquartile Range		18268,0200	
	Skewness		-,045	,089
	Kurtosis		-,979	,178
XU030 Index PX_LAST	Mean		117268,7564	573,0346511
	95% Confidence Interval for Mean	Lower Bound	116143,8186	
		Upper Bound	118393,6943	
	5% Trimmed Mean		117188,7057	
	Median		117872,3000	
	Variance		247261639,6	
	Std. Deviation		15724,55531	
	Minimum		88280,4300	
	Maximum		147935,8000	
	Range		59655,3700	
	Interquartile Range		23878,9000	
	Skewness		-,137	,089
	Kurtosis		-1,016	,178

Table 5.2: Descriptives (Cryptocurrencies)

Descriptives

			Statistic	Std. Error
XBTUSD BGN Curncy PX_LAST	Mean		6216,866246	112,9540461
	95% Confidence Interval for Mean	Lower Bound	5994,629215	
		Upper Bound	6439,103277	
	5% Trimmed Mean		6134,084082	
	Median		6400,960000	
	Variance		4044481,442	
	Std. Deviation		2011,089616	
	Minimum		3156,8900	
	Maximum		11705,7200	
	Range		8548,8300	
	Interquartile Range		3539,5000	
	Skewness		,295	,137
	Kurtosis		-,624	,273
XET BGN Curncy PX_LAST	Mean		339,847991	13,0604975
	95% Confidence Interval for Mean	Lower Bound	314,151468	
		Upper Bound	365,544513	
	5% Trimmed Mean		323,560732	
	Median		224,697000	
	Variance		54072,781	
	Std. Deviation		232,5355476	
	Minimum		81,7900	
	Maximum		936,6420	
	Range		854,8520	
	Interquartile Range		359,4625	
	Skewness		,846	,137
	Kurtosis		-,443	,273
XLCUSD BGN Curncy PX_LAST	Mean		82,888044	2,8080869
	95% Confidence Interval for Mean	Lower Bound	77,363135	
		Upper Bound	88,412954	
	5% Trimmed Mean		78,883521	
	Median		60,930000	
	Variance		2499,657	
	Std. Deviation		49,9965652	
	Minimum		22,6200	
	Maximum		243,7400	
	Range		221,1200	
	Interquartile Range		68,4635	
	Skewness		1,077	,137
	Kurtosis		,338	,273
XRP BGN Curncy PX_LAST	Mean		,481518	,0110828
	95% Confidence Interval for Mean	Lower Bound	,459712	
		Upper Bound	,503323	
	5% Trimmed Mean		,464210	
	Median		,439000	
	Variance		,039	
	Std. Deviation		,1973233	
	Minimum		,2585	
	Maximum		1,1306	
	Range		,8721	
	Interquartile Range		,2450	
	Skewness		1,239	,137
	Kurtosis		,850	,273

There are outliers in BTC, LTC and XPR price data and they have been excluded in Kolmogorov-Smirnov (K-S) and Shapiro-Wilk tests. The result found is the same with the test measures calculated manually in Excel with and without outliers. As it can be seen from the results, the distributions' shapes are not belly curved.

In the table 5.3, both normality tests are depicted:

Table 5.3: Normality test

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
SPX Index PX_LAST	,154	753	,000	,922	753	,000
NDX Index PX_LAST	,154	753	,000	,924	753	,000
XU100 Index PX_LAST	,111	753	,000	,957	753	,000
XU030 Index PX_LAST	,115	753	,000	,951	753	,000

a. Lilliefors Significance Correction

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
XBTUSD BGN Curncy PX_LAST	,135	317	,000	,943	317	,000
XET BGN Curncy PX_LAST	,203	317	,000	,869	317	,000
XLCUSD BGN Curncy PX_LAST	,177	317	,000	,880	317	,000
XRP BGN Curncy PX_LAST	,144	317	,000	,855	317	,000

a. Lilliefors Significance Correction

For both tests, if the p value found is smaller than 0.05 significance level (it is chosen as $\alpha=0.05$ or confidence level is 95 percent), then the Null hypothesis is rejected and the sample is not normally distributed. For each index and cryptocurrency, p value was same for both tests. To be much more precise, $0.00<0.05$ is used for all cryptocurrencies and indexes. According to Kolmogorov-Smirnov and Sharpiro-Wilk tests, the price distribution of S&P500, Nasdaq, BIST30, BIST100, BTC, ETH, LTC and XRP are not normally distributed.

5.1.2 Normal Q-Q Plot Analysis

According to Normal Quantile-Quantile Plot analysis, dots or circles should be closer to the linear line. Points frequently deviating from the line show that the sample is not normally distributed.

Figure 5.1 shows four indices' Normal Q-Q Plot analysis. S&P500, Nasdaq, BIST100 and BIST30 have the points deviating from the linear line or the prices create circles that do not lie on the linear line which shows the S&P500, Nasdaq, BIST100 and BIST30 prices are not normally distributed. To conclude, as it is stated in the first test, Normal Q-Q plot also supports the fact that index prices are not normally distributed.

Figure 5.1: Normal Q-Q plot analysis (S&P500, Nasdaq, BIST30 and BIST100 accordingly)

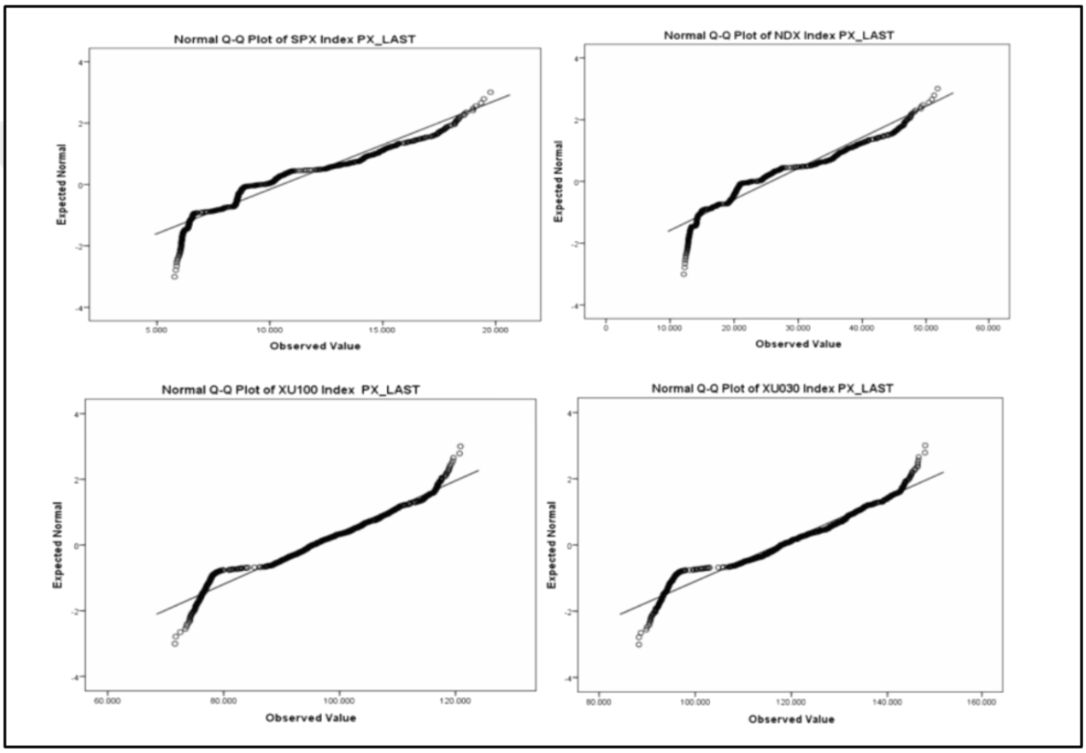
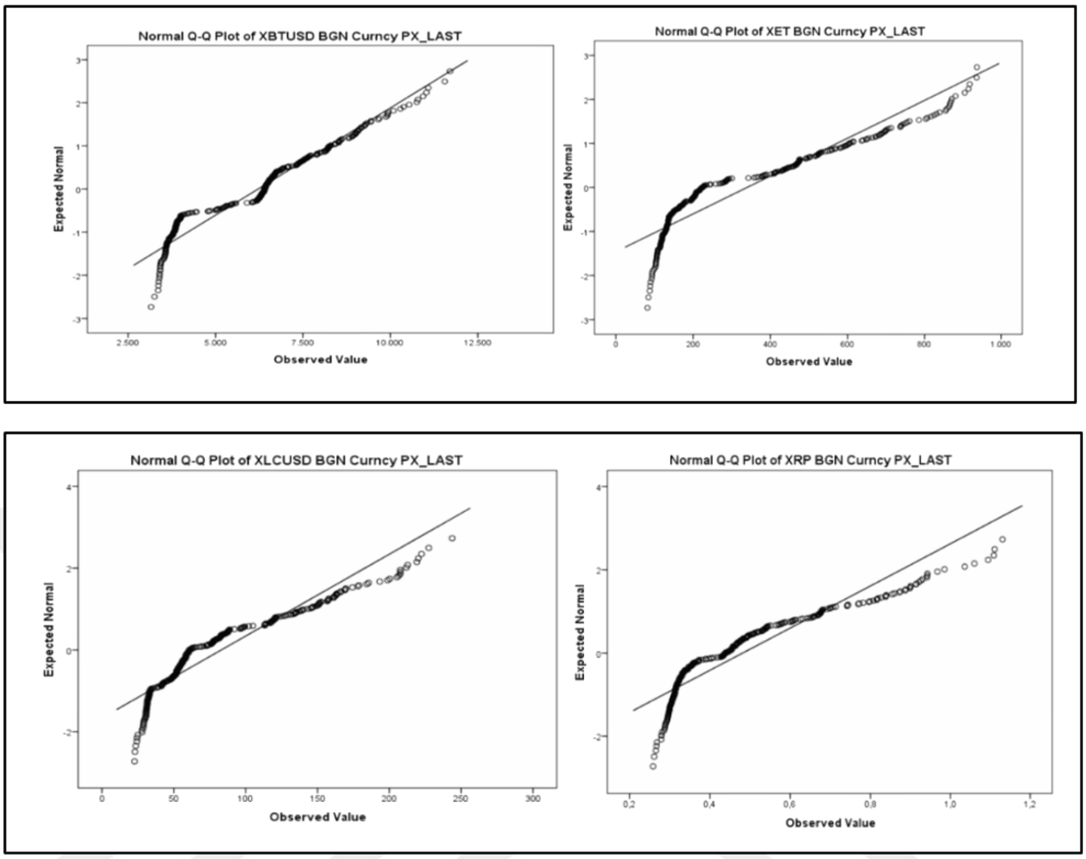


Figure 5.2, on the other hand, shows the Normal Q-Q Plot of the selected cryptocurrencies. Apparently, none of the graphs fit the linear line for 4 cryptocurrencies and price distributions are not normal. Hence, the Null hypothesis is rejected for both index and cryptocurrency price data.

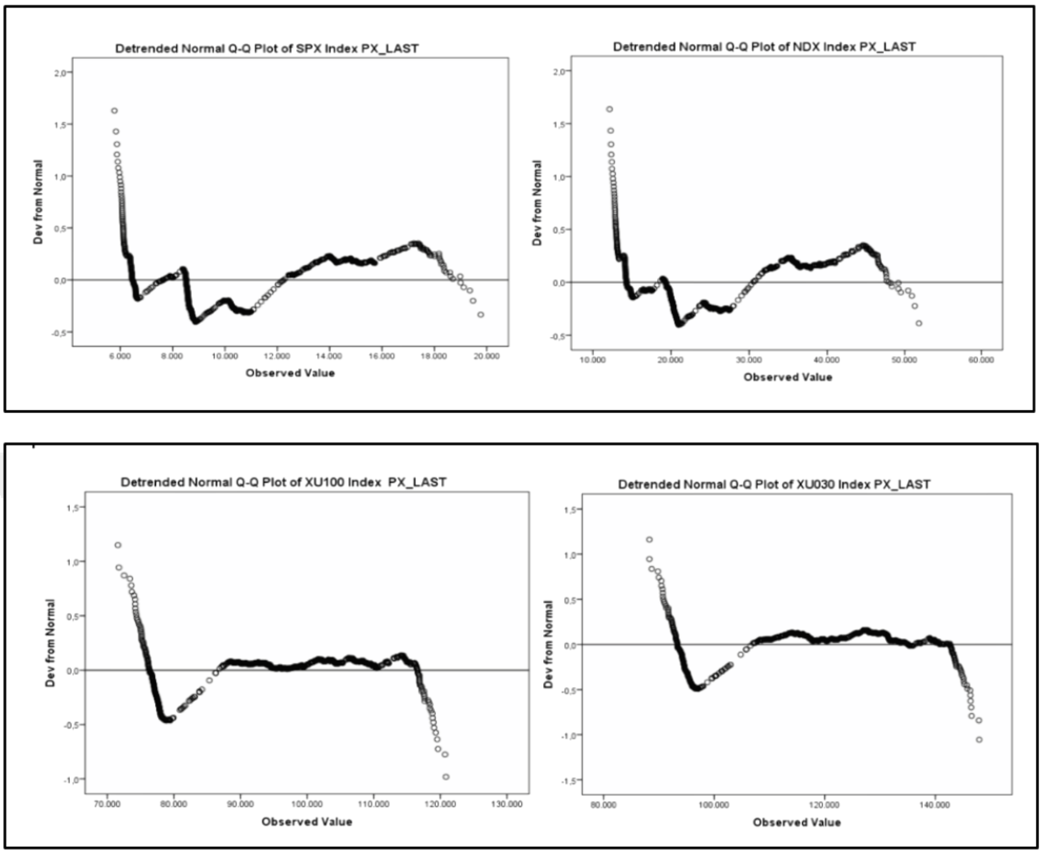
Figure 5.2: Normal Q-Q plot analysis (BTC, ETH, LTC, XRP accordingly)



5.1.3 Detrended Q-Q Plot Analysis

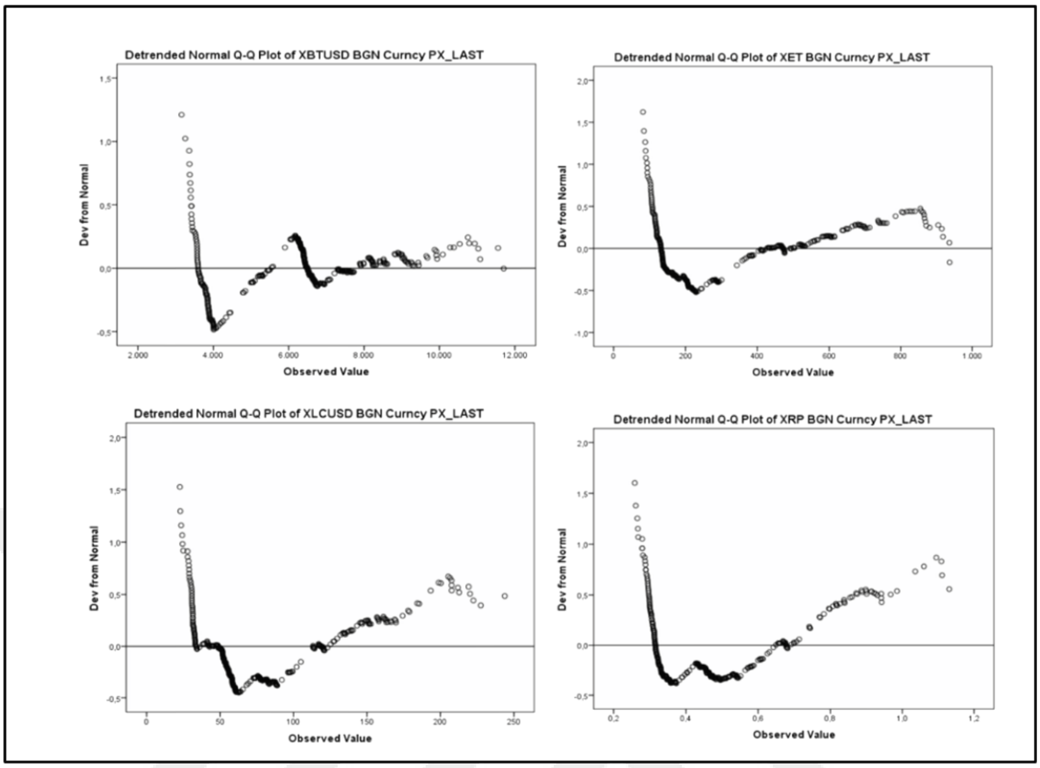
For Detrended Q-Q Plot analysis, price dots or circles should stay on the horizontal line to clarify the existence of the normal distribution. However, as it can be seen from the tables, none of the graphs created by price dots do not lie on the horizontal line, thereupon, none of the samples are normally distributed.

Figure 5.3: Detrended Q-Q plot analysis (S&P500, Nasdaq, BIST30 and BIST100 accordingly)



At the same time, according to Detrended Q-Q Plot analysis shown on Figure 5.4, none of the stated cryptocurrencies have a Normal Distribution. The only difference between indices and cryptocurrency samples is that in the case of cryptocurrencies the deviation from the horizontal line is considerably high compared to index prices.

Figure 5.4: Detrended Q-Q plot analysis (BTC, ETH, LTC, XRP accordingly)



5.1.4 Histogram Analysis

Before providing histogram of each sample, it is crucial to have a look at the descriptive variables of these samples. Moreover, the main contributors of the histogram are the mean and standard deviation. In order to infer skewness, or kurtosis and to check distributions' shape, the location of prices relative to the mean and standard deviation is essential.

By looking at the descriptive statistics, we can conclude that none of the tables are normally distributed. However, the tails and skewness value depict that S&P500 and Nasdaq has similarity to BTC and ETH price data and their price sample are similarly distributed.

Figure 5.5: Histogram (S&P500, Nasdaq, BIST100 and BIST30 accordingly)

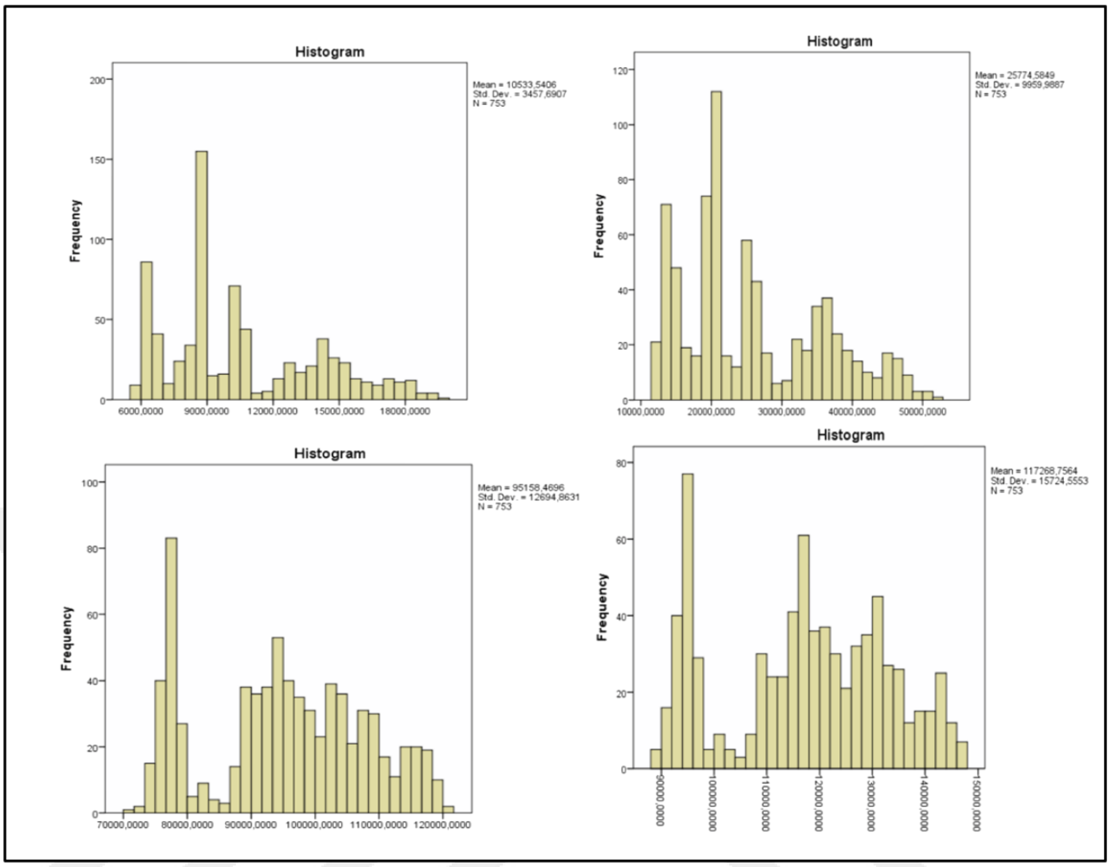
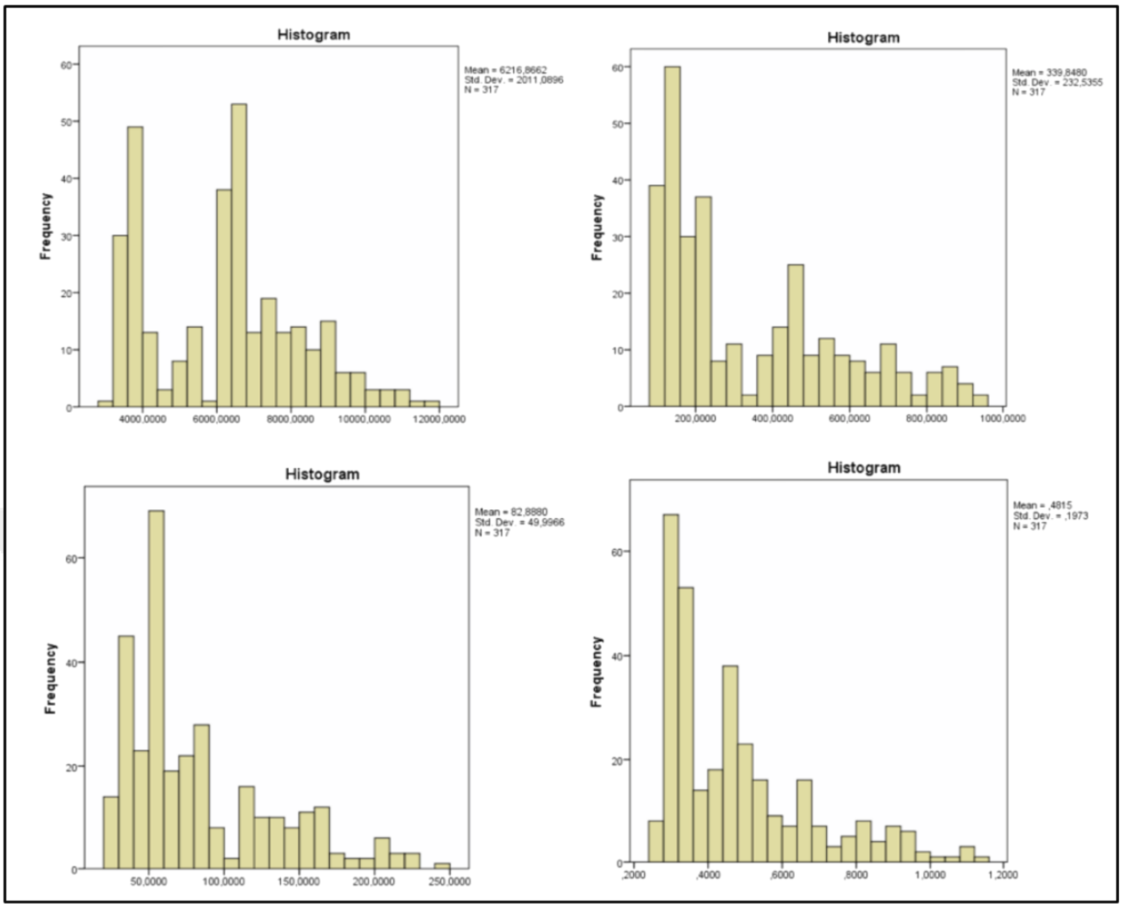


Figure 5.6: Histogram (BTC, ETH, LTC, XRP accordingly)



Since the tables above are not symmetrically distributed around the mean, none of them are normally distributed. However, there is a difference in the shape of the distribution. S&P500, Nasdaq, BTC, ETH, LTC and XRP have a histogram with a positive or right skewness which means right tail is longer than the left tail and the mean value is higher than the median value. However, BIST100 and BIST30 have mean and median value lower than mode value and their histogram is negatively skewed and there is left skewness. On the other hand, except BTC, LTC and XRP, other price tables have light tails meaning negative kurtosis which means they have no or less outliers.

To summarize, in order to claim the data is normally distributed skewness of the table should be equal to zero or very close to zero. However, those tables do not prove that premise. Some are moderately skewed in the case of S&P500, Nasdaq and ETH. Some are highly skewed in the case of BTC, LTC and XRP. Furthermore, normally distributed table have a kurtosis equal to 3. However, some of the tables including BTC, LTC and XRP have positive kurtosis lower than 3 which means that extreme values or outliers are more than the other tables. Generally positive kurtosis shows heavier tails and sudden not flatter peaks.

5.1.5 Box Plot Analysis

The box plot displays the height of each quartile and by calculating upper and lower fence, outliers can be removed from the distribution sample. Upper level is calculated as the summation of the third quartile and 1.5 times interquartile and lower level is the difference between the first quartile and 1.5 times interquartile. However, with SPSS, outliers can be easily detected and eliminated from the distribution to avoid extra misguiding noise.

Figure 5.7: Box plot (S&P500, Nasdaq, BIST100 and BIST30 accordingly)

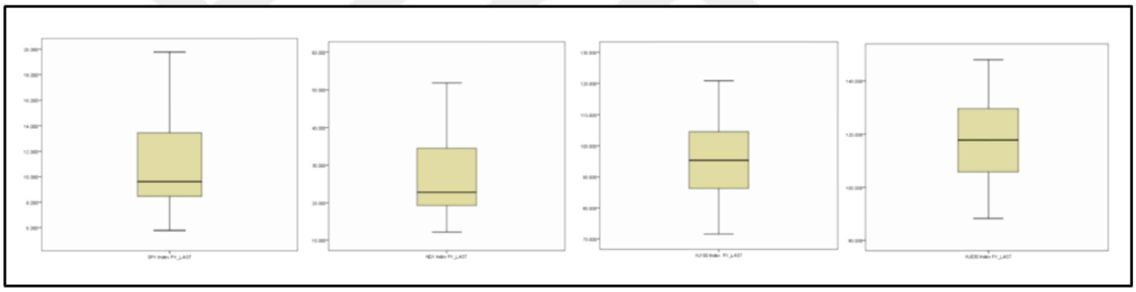
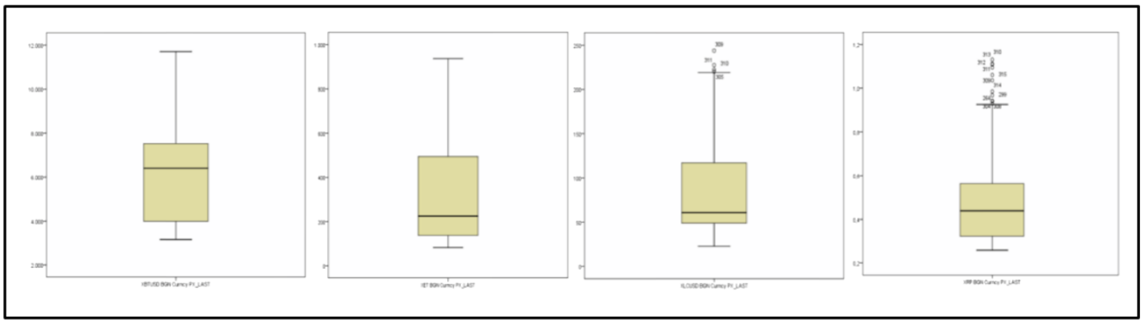


Figure 5.8: Box plot (BTC, ETH, LTC, XRP accordingly)



In this sample case only LTC and XRP has outliers. Excluding BIST100 and BIST30 which have almost symmetrical distribution, other tables illustrates higher upper tail and not normal distribution.

5.2 REGRESSION ANALYSIS AMONG CRYPTOCURRENCY PRICESS

For further research about the correlation of indices of cryptocurrencies, one locomotive cryptocurrency can be taken into consideration. However, in order to select such currency, the correlation of that cryptocurrency with others should be checked. For that purpose, the regression analysis is conducted among BTC and other three specified cryptocurrencies which are XRP, LTC and ETH and validity of the analysis is confirmed.

In regression analysis, Multiple R shows correlation coefficient by measuring the strength of a linear relationship between two separate variables. The correlation coefficient is expected to be any value between -1 and 1 and as long as the absolute value is closer to 1, then the relationship is stronger. Also 0 shows no relationships at all.

R^2 shows the coefficient of determination and is utilized as an indicator for the goodness of fit by displaying how many points indeed fall on the regression line.

Standard Error illustrates how precise the regression analysis is. As long as the number is small, regression equation is expected to be accurate.

Ripple (XRP) calculates a Multiple R of 0.86 with BTC which is close to 1 and it means there is a strong positive relationship between BTC and XRP when BTC prices are taken as independent and XRP prices are taken as dependent variables. R^2 is 0.74 and this means that 74 percent of XRP price data can be explained by BTC price data. Finally, the standard error is 0.1 as a small number, it ascertains the accuracy of the regression analysis. On the other hand, Significant F value being smaller than 5 percent also attenuates that the regression analysis is accurate.

Figure 5.9: BTC XRP regression line

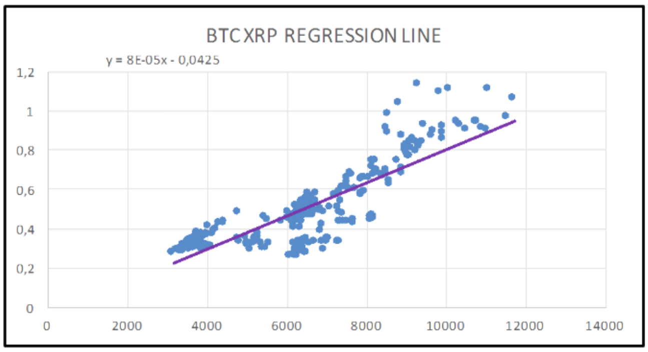


Table 5.4: Regression analysis (XRP&BTC)

SUMMARY OUTPUT BTC XRP	
Regression Statistics	
Multiple R	0.859126569
R Square	0.738098461
Adjusted R Square	0.73726438
Standard Error	0.101153234
Observations	316

Litecoin (LTC) also has a Multiple R which is 0.89 and is demonstrates a strong positive relationship with BTC price data. R^2 is 0.79 and 79 percent of LTC price data can be explained by BTC price data or BTC price movements. However, Significant F value is lower than 5 percent, standard error is higher compared to regression analysis done between BTC and XRP prices. On the other hand, the standard error of 23.1 is not a considerably bigger number.

Figure 5.10: BTC LTC regression line

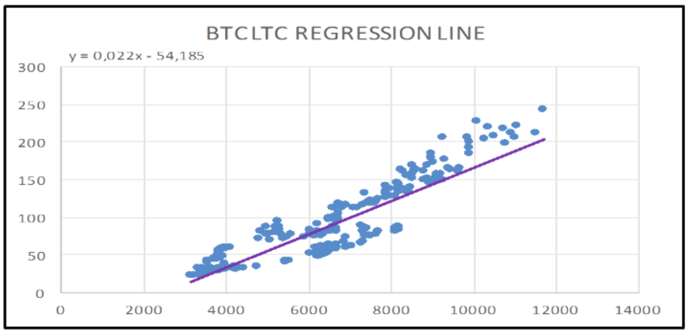


Table 5.5: Regression analysis (LTC&BTC)

SUMMARY OUTPUT LTC	
Regression Statistics	
Multiple R	0.886980916
R Square	0.786735146
Adjusted R Square	0.786055958
Standard Error	23.15992364
Observations	316

On the other hand, a Multiple R of 0.91 shows highly strong positive relationship and higher R^2 demonstrates the fact that 83 percent of Ethereum (ETH) prices can be explained with BTC prices, Standard error of the analysis is relatively high and it is 95.4. It has a considerably symmetric price distribution.

Figure 5.11: BTC ETH regression line

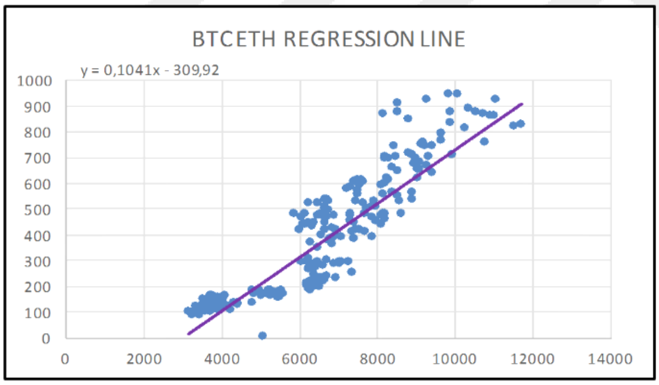


Table 5.6 Regression analysis (ETH&BTC)

SUMMARY OUTPUT ETH	
Regression Statistics	
Multiple R	0.912375413
R Square	0.832428893
Adjusted R Square	0.831895227
Standard Error	95.39228802
Observations	316

After checking the relationship between specific cryptocurrencies and BTC, in SPSS, a general linear regression analysis showing overall correlation between these three cryptocurrencies and BTC has been conducted.

Table 5.7: Regression analysis summary

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,918[a]	,842	,840	803,1984345

a. Predictors: (Constant), XRP BGN Curncy PX_LAST , XLCUSD BGN Curncy PX_LAST , XET BGN Curncy PX_LAST

b. Dependent Variable: XBTUSD BGN Curncy PX_LAST

This table indicates that there is a very strong positive relationship betwixt ETH, LTC and XRP trio and BTC; in other words, BTC plays locomotive role for these three cryptocurrencies. Moreover, 84.2 percent of these cryptocurrency prices can be explained by BTC price movements.

Table 5.8: Correlation

		XBTUSD BGN Curncy PX_LAST	XET BGN Curncy PX_LAST	XLCUSD BGN Curncy PX_LAST	XRP BGN Curncy PX_LAST
Pearson Correlation	XBTUSD BGN Curncy PX_LAST	1,000	,912	,887	,859
	XET BGN Curncy PX_LAST	,912	1,000	,936	,915
	XLCUSD BGN Curncy PX_LAST	,887	,936	1,000	,906
	XRP BGN Curncy PX_LAST	,859	,915	,906	1,000
Sig. (1-tailed)	XBTUSD BGN Curncy PX_LAST	.	,000	,000	,000
	XET BGN Curncy PX_LAST	,000	.	,000	,000
	XLCUSD BGN Curncy PX_LAST	,000	,000	.	,000
	XRP BGN Curncy PX_LAST	,000	,000	,000	.
N	XBTUSD BGN Curncy PX_LAST	317	317	317	317
	XET BGN Curncy PX_LAST	317	317	317	317
	XLCUSD BGN Curncy PX_LAST	317	317	317	317
	XRP BGN Curncy PX_LAST	317	317	317	317

The table above proves the results found in Excel regression analysis shown in Figures 5.9, 5.10 and 5.11. Also, Anova test judging F value in order to check how accurate the analysis is proved with smaller value than the alpha value. Therefore, it can be concluded that there is strong positives correlation among these three cryptocurrencies and BTC.

5.3 REGRESSION ANALYSIS BETWEEN BTC PRICES AND SPECIFIC INDEX VALUES.

Table 5.4 illustrates the fact that there is a strong relationship betwixt stock prices (indexes) and BTC prices. Since BTC has a strong correlation with other three cryptocurrencies, it can be also stated that there is a positive relationship between them and these indices, as well. However, this relationship is not as strong as the previous correlation among cryptocurrencies.

Table 5.9: Regression analysis (BTC&Indices)

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,807[a]	,651	,649	2182,301425

a. Predictors: (Constant), XU030 Index PX_LAST , SPX Index PX_LAST , NDX Index PX_LAST , XU100 Index PX_LAST

b. Dependent Variable: XBTUSD BGN Curncy PX_LAST

On the other hand, table 5.5 shows that the correlation between BTC and BIST100 (r=0.751) and BIST30 (r=0.745) is stronger than S&P500 (r=0.429) or Nasdaq (r=0.443).

Table 5.10: Correlations

		XBTUSD BGN Curncy PX_LAST	SPX Index PX_LAST	NDX Index PX_LAST	XU100 Index PX_LAST	XU030 Index PX_LAST
Pearson Correlation	XBTUSD BGN Curncy PX_LAST	1,000	,429	,443	,751	,745
	SPX Index PX_LAST	,429	1,000	,998	,367	,409
	NDX Index PX_LAST	,443	,998	1,000	,383	,424
	XU100 Index PX_LAST	,751	,367	,383	1,000	,998
	XU030 Index PX_LAST	,745	,409	,424	,998	1,000
Sig. (1-tailed)	XBTUSD BGN Curncy PX_LAST	.	,000	,000	,000	,000
	SPX Index PX_LAST	,000	.	,000	,000	,000
	NDX Index PX_LAST	,000	,000	.	,000	,000
	XU100 Index PX_LAST	,000	,000	,000	.	,000
	XU030 Index PX_LAST	,000	,000	,000	,000	.
N	XBTUSD BGN Curncy PX_LAST	753	753	753	753	753
	SPX Index PX_LAST	753	753	753	753	753
	NDX Index PX_LAST	753	753	753	753	753
	XU100 Index PX_LAST	753	753	753	753	753
	XU030 Index PX_LAST	753	753	753	753	753

6. CONCLUSION AND DISCUSSION

All three hypotheses have been checked. The distributions of the price tables are analyzed and various sources have been utilized in order to end up with a far more accurate empirical result. Thus, after meticulous search, the premise that the price distributions of S&P500, Nasdaq, BIST100 and BIST30 are proven to be non-normal. This posits that there is no rational decision-making process among investors and this abnormality is a signal demonstrating on behavioral finance's one of the main arguments. Cognitive biases are viable in the cryptocurrency market.

Secondly, the correlation among cryptocurrency investors is analyzed and the result shows there is strong positive correlation between ETH, LTC, XRP and BTC prices. Additionally, as long as the market price is increasing or closer to BTC, that cryptocurrency has relatively higher correlation with BTC and it is more likely to be sensitive to price movements and to immediate volatility in BTC prices. The ETH has a correlation higher than LTC and accordingly XRP. Briefly, it states that BTC plays locomotive role relative to other cryptocurrency prices and they are very sensitive to the changes in BTC prices.

Thirdly, there is correlation between indices and BTC price distribution. Even though S&P500 and Nasdaq has very small positive correlation with BTC, BIST 100 and BIST30 care good indicators for any movement expectations in BTC since there is almost a perfect correlation between BTC prices and BIST100 and BIST30 prices. This is vital from the perspective of supporting the main objective of this research. If cryptocurrencies and indices have the same distribution and if they are positively correlated, then commonly observed cognitive biases among stock investors can be the characteristics of cryptocurrency investors, as well.

When all this information is taken into consideration, after being sure that both cryptocurrencies and these indices have similar irrational-decision making problem because of price anomalies or sensitivity. Further analysis can be conducted to quantitatively check biases among cryptocurrency investors. The biases mentioned in literature review, are proven to exist among cryptocurrency investors specifically for BTC. However, because of anonymity, it is hard to check validity of the results. There are methods showing how these biases can be calculated and tested using quantitative data and indeed they have been analyzed on the basis of stock investors' data. API's can be derived from variety of the exchanges and cryptocurrency investors can be empirically tested. This thesis can guide future research since it already provided quantitative analysis in 30 minute intervals (because of high volatility, it is crucial to have at least 30-minute interval since daily data is too broad.), the biases can be analyzed. If they can be detected, then investors can be informed about these anomalies so that they try avoid these biases and this can, in fact, result in amelioration in portfolio performances.

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APPENDICES

APPENDIX 1: Table 1 Extreme Values of the Data Samples

Extreme Values

			Case Number	Value
SPX Index PX_LAST	Highest	1	177	19771,0060
		2	164	19477,3165
		3	162	19356,1727
		4	163	19121,8873
		5	161	19001,7885
	Lowest	1	753	5775,6114
		2	752	5833,4157
		3	713	5870,7847
		4	751	5871,3193
		5	712	5902,2177
NDX Index PX_LAST	Highest	1	177	51854,0702
		2	164	51310,5936
		3	162	50933,1178
		4	163	50445,8072
		5	161	49489,5089
	Lowest	1	753	12140,4426
		2	752	12279,0426
		3	713	12328,4160
		4	751	12353,4309
		5	712	12437,2057
XU100 Index PX_LAST	Highest	1	314	120845,3000
		2	315	120701,9000
		3	317	119648,4000
		4	312	119528,8000
		5	313	119303,1000
	Lowest	1	698	71594,9800
		2	697	71738,4300
		3	608	72519,8500
		4	607	73390,9400
		5	606	73599,7000
XU030 Index PX_LAST	Highest	1	314	147935,8000
		2	315	147880,2000
		3	292	146553,9000
		4	312	146480,5000
		5	293	146366,9000
	Lowest	1	697	88280,4300
		2	698	88284,3600
		3	608	88691,4200
		4	607	89808,2800
		5	606	89980,2100

Extreme Values

			Case Number	Value
XBTUSD BGN Curncy PX_LAST	Highest	1	309	11705,7200
		2	300	11555,9900
		3	310	11081,4100
		4	301	11029,9500
		5	302	10933,7500
	Lowest	1	96	3156,8900
		2	97	3254,8100
		3	57	3358,9100
		4	58	3366,3100
		5	99	3373,7800
XET BGN Curncy PX_LAST	Highest	1	311	936,6420
		2	310	935,9320
		3	312	917,9920
		4	309	914,7170
		5	313	904,7100
	Lowest	1	96	81,7900
		2	97	84,3400
		3	99	87,9100
		4	100	89,0570
		5	98	89,8970
XLCUSD BGN Curncy PX_LAST	Highest	1	309	243,7400
		2	311	227,4320
		3	310	222,4200
		4	305	220,1380
		5	304	219,1520
	Lowest	1	96	22,6200
		2	97	22,8950
		3	99	23,4800
		4	100	24,2350
		5	98	24,4450
XRP BGN Curncy PX_LAST	Highest	1	313	1,1306
		2	311	1,1108
		3	310	1,1087
		4	312	1,0945
		5	309	1,0601
	Lowest	1	164	,2585
		2	184	,2612
		3	165	,2656
		4	160	,2670
		5	163	,2680

APPENDIX 2: Table 2: Regression Analysis among Cryptocurrencies - Case Processing Summary

Case Processing Summary

	Cases					
	Valid		Missing		Total	
	N	Percent	N	Percent	N	Percent
XBTUSD BGN Curncy PX_LAST	317	40,6%	464	59,4%	781	100,0%
XET BGN Curncy PX_LAST	317	40,6%	464	59,4%	781	100,0%
XLCUSD BGN Curncy PX_LAST	317	40,6%	464	59,4%	781	100,0%
XRP BGN Curncy PX_LAST	317	40,6%	464	59,4%	781	100,0%

Table 3: Coefficient

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.	95,0% Confidence Interval for B Lower Bound	95,0% Confidence Interval for B Upper Bound
1	(Constant)	3225,987	147,337		21,895	,000	2936,091	3515,883
	XET BGN Curncy PX_LAST	5,382	,619	,622	8,691	,000	4,163	6,600
	XLCUSD BGN Curncy PX_LAST	9,396	2,742	,234	3,427	,001	4,002	14,791
	XRP BGN Curncy PX_LAST	795,465	605,555	,078	1,314	,190	-396,008	1986,939

a. Dependent Variable: XBTUSD BGN Curncy PX_LAST

Table 4: Anova test

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	1076131158	3	358710385,9	556,030	,000[b]
	Residual	201924978,0	313	645127,725		
	Total	1278056136	316			

a. Dependent Variable: XBTUSD BGN Curncy PX_LAST

b. Predictors: (Constant), XRP BGN Curncy PX_LAST , XLCUSD BGN Curncy PX_LAST , XET BGN Curncy PX_LAST

APPENDIX 3: Table 5: Regression Analysis between Indexes and BTC - Case Process Summary

Case Processing Summary

	Cases					
	Valid		Missing		Total	
	N	Percent	N	Percent	N	Percent
SPX Index PX_LAST	753	96,4%	28	3,6%	781	100,0%
NDX Index PX_LAST	753	96,4%	28	3,6%	781	100,0%
XU100 Index PX_LAST	753	96,4%	28	3,6%	781	100,0%
XU030 Index PX_LAST	753	96,4%	28	3,6%	781	100,0%

Table 9: Coefficients

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95,0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	-15365,446	1077,190		-14,264	,000	-17480,120	-13250,771
	SPX Index PX_LAST	-,382	,446	-,358	-,855	,393	-1,258	,495
	NDX Index PX_LAST	,286	,155	,773	1,846	,065	-,018	,590
	XU100 Index PX_LAST	1,545	,125	5,324	12,340	,000	1,299	1,790
	XU030 Index PX_LAST	-1,112	,103	-4,748	-10,823	,000	-1,314	-,910

a. Dependent Variable: XBTUSD BGN Curncy PX_LAST

Table 10: Anova Test

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	6638621155	4	1659655289	348,488	,000[b]
	Residual	3562304753	748	4762439,509		
	Total	10200925907	752			

a. Dependent Variable: XBTUSD BGN Curncy PX_LAST

b. Predictors: (Constant), XU030 Index PX_LAST , SPX Index PX_LAST , NDX Index PX_LAST , XU100 Index PX_LAST