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# Influence of anchoring bias on Bitcoin investors' trading decisions

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**Abstract**

Blockchain has been perceived by many professionals as the next revolution of humankind. Its application spreads across multiple industries and aspects of life, but the first impact was to be found in finance. In 2017, cryptocurrency became a new financial phenomenon around the globe when Bitcoin's value skyrocketed to the peak of \$19.535. Many investors, both professional and amateur, have taken part in this modern trend of trading. Unfortunately, a number of those experienced losses due to various reasons. Among which a prominent heuristic called "anchoring" might be one of the causes of incorrect assessment leading to potential damages. Several studies in the past have validated the existence of anchoring bias in conventional stock market. However, current literature failed to address similar effect in cryptocurrency market. This thesis examines the presence of Bitcoin price anchoring in trading decisions of investors. Order dataset, including bids and asks, were collected from Kraken exchange to serve the analysis purpose. The analysis has confirmed that investors' trading decisions anchored to changes in Bitcoin market price. Furthermore, the result tells that anchoring bias influenced investors' valuation of price differently when they placed bid or ask orders. Nonetheless, its impact does not vary between bull and bear market situations. In conclusion, investors should be well aware of anchoring bias when making trading decisions. The heuristic can lead to both negative and positive consequences, depending on investor's perception toward it.

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**Keywords** Bitcoin, Blockchain, cryptocurrency, anchoring bias, heuristic

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## Glossary

**Application Programming Interface (API)** – A set of rules that allows programmers to develop software for a particular operating system without having to be completely familiar with that operating system (Merriam-Webster, 2018).

**Asks** - The ask is the price a seller is willing to accept for a security, which is often referred to as the offer price. Along with the price, the ask quote might also stipulate the amount of the security available to be sold at the stated price (Investopedia, 2018).

**Bids** - A bid is an offer made by an investor, a *trader* or a *dealer* to buy a security, commodity or currency. It stipulates both the price the potential buyer is willing to pay and the quantity to be purchased at that price (Investopedia, 2018).

**Bull / Bear market** - A bull market is represented by a rising price trend, and a bear market is indicated by a falling price trend (Investopedia, 2018).

**Cryptocurrency** - Any form of currency that only exists digitally, that usually has no central issuing or regulating authority but instead uses a decentralized system to record transactions and manage the issuance of new units, and that relies on cryptography to prevent counterfeiting and fraudulent transactions (Merriam-Webster, 2018).

**Market capitalization** - The market capitalization is the value of all the units of a cryptocurrency that are for sale on the market right now. It is a strong indicator of demand because it shows you how much money has been invested in a particular altcoin. (Cryptoincome, 2017).

**Momentum investing** – Momentum investing is a strategy aims to capitalize on the continuance of existing trends in the market. It does not consider operational performance but rather looks for patterns that confirm the trend continuation (Investopedia, 2018).

**SPSS** - IBM SPSS platform offers advanced statistical analysis, a vast library of machine learning algorithms, text analysis, open source extensibility, integration with big data and seamless deployment into applications (IBM, 2018).

## 1 Introduction

During recent years, many organizations and individuals tried migrating physical monetary bills and coins to digital world with the help of computers. Some attempts were successful enabling banks to turn money into numbers on the screen, online shoppers to pay their bills via a mouse click or restaurant cashiers to receive payments with a single swipe of credit card. These innovations were carried out with various technologies. Nevertheless, they all possess one common characteristics of being backed by banking system or other system as third parties. These entities always stay in the middle of any digitalized transactions, limiting the speed of transferring money, and in most cases, incurring additional costs to transaction participating counterparts. In 2009, a revolutionary invention arose by an anonymous programmer, or a group of programmers, named Nakamoto Satoshi. It removes the influence of third parties from all online transactions and created a new currency called cryptocurrency with Bitcoin as the initial coin. However, not everyone was interested in this new phenomenon, in fact, no one was interested for a long time. Until recently, in the second half of 2017, Bitcoin price has been skyrocketing, making the whole market with other cryptocurrencies (See Glossary) flourish at its best ever since. Consequently, media and the press reported stories of this exciting topic in the news with different points of view, both negative and positive. Regardless of pessimistic attitudes of some people, the public expectation was filled with huge profit brought by investing in cryptocurrency.

The rapid increase in number of investors caused even higher prices, or some might argue as over pricing, of cryptocurrencies' values, specifically Bitcoin value. Whilst many conventional equity investors were professional, or at least knowledgeable, majority of Bitcoin investors stepped in the market with less experience and sometimes no fundamental comprehension of what they were investing in due to the complexity of cryptocurrency ideology and short research time. As a Bitcoin investor in this rising trend, the author finds himself occasionally lost in this trading decision. A popular, but not well-known, heuristic called “anchoring bias” was found at the heart of many investors' decision-making behavior. The author also suffers from such effect and wondered if other investors fall for similar effect. Therefore, this study is conducted to investigate such phenomenon.



## 1.1 Research question

Researching the anchoring bias is not new in the field of psychology and behavior studies. However, the type of subjects was vast on various topics. However, only a few were conducted in the finance sector, and even fewer in cryptocurrency market. Hence, this study is in fact quite new in the sense of studied subjects and the context. Author does not aim to investigate complicated high financiers in the market paradigm, but focuses on ordinary investors. Thus three simple questions will be studied.

- Is there an anchoring bias in Bitcoin market?
- Does anchoring bias influence differently on bids and asks (See Glossary)?
- How does anchoring bias affect trading decisions in market fluctuations?

## 1.2 Aims of study

This thesis aims to provide academic evidence of anchoring bias existence in Bitcoin investments. Further explanations would be given on different influences of such phenomenon on various subjects in different periods of the market. Based on those conclusions, the author wishes to raise investors' awareness about the negative or positive impact created from this heuristic. Investors may either prevent themselves from suffering losses or gain profits from utilizing it in appropriate occasions.

## 1.3 Scope of study

The subjects of this thesis are ordinary investors from all areas of industry. Due to the fact that Bitcoin investors' identities are confidential, it is challenging to identify or verify their real personal information. Therefore, data collection based on direct interaction with them is barely feasible.

Another limitation lies with the lack of versatility from Bitcoin exchange platforms. Merely Kraken exchange provides comprehensive and informative APIs to collect data. Hence, the study is limited to customers of Kraken only. However, since it is one of the biggest credible names in the field, investors variety is guaranteed.

## 2 Literature Review

### 2.1 Cryptocurrency market

#### 2.1.1 The high tide of cryptocurrency

Several years ago, only a fraction of people in the world knew about cryptocurrency and even less acknowledged its potential in future. In recent time, especially in a few months from mid-2017 to early 2018, many people began to learn more about cryptocurrency as the press kept posting incredible news regarding the booming price of many cryptocurrencies. The tide of cryptocurrency market has risen tremendously high, as never before, triggering the attention of investors from all fields and classes. At the time of this writing (January 10, 2018) the total market capitalization (See Glossary) of 1398 cryptocurrencies in market is more than 712 billion US dollars (Cryptocurrency Market Capitalizations – All Cryptocurrencies, 2018), almost 50 times bigger than 1 year ago.

However, the development of this market was not happening gradually but it has started to explode only since mid of 2017. Figure 1 shows that during the time from mid-2013 to mid-2017, market capitalization experienced minor changes but in the latter part of 2017, this figure made hyper jumps setting new records all the time before losing almost half of its value in the first quarter of 2018.

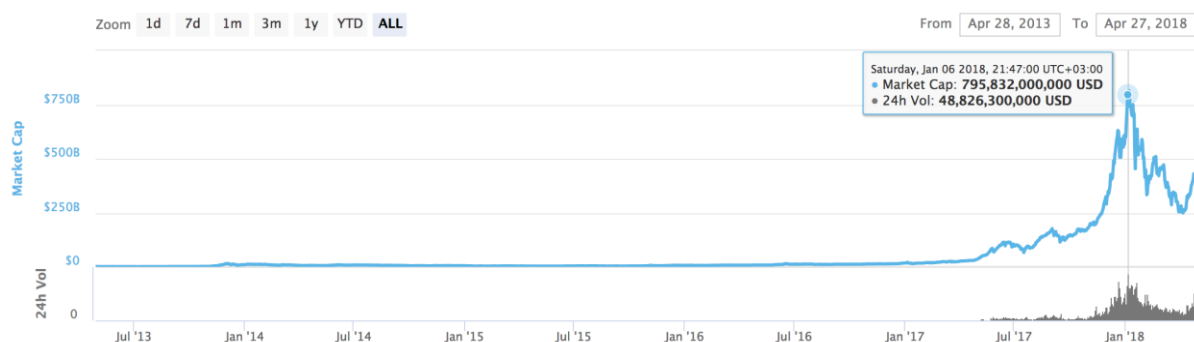
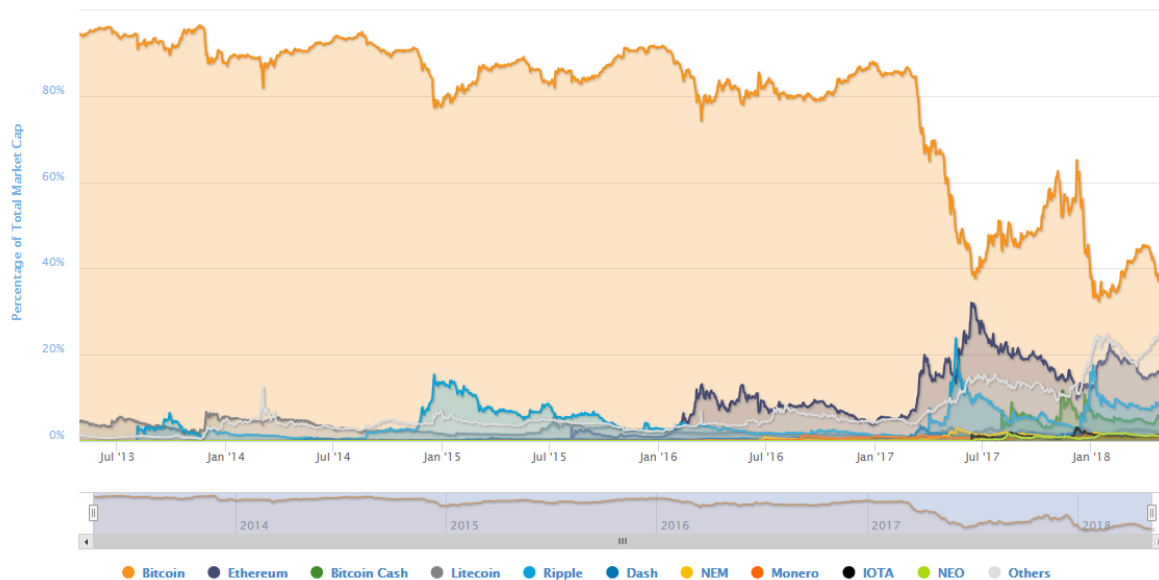


Figure 1 - Total market capitalization

(Cryptocurrency Market Capitalizations – Global Chart, 2018)

Similar to every other market, there are always one or more dominant players that account for majority of market capitalization. In case of cryptocurrency, the outstanding dominant is Bitcoin. Figure 2 expresses the significant domination of Bitcoin – marked with orange color - over other cryptocurrencies. There was an obvious change in recent months

when other currencies' market capitalizations have arisen and taken more share in the big picture. However, Bitcoin market capitalization is still the largest one and has tremendous impact on other coins' value. As of December 17, 2017, Bitcoin price reaches its current top at \$19.535 with market capitalization of 318 billion dollars.



*Figure 2 - Dominance of Total Market Capitalization*

*(Cryptocurrency Market Capitalizations – Global Chart, 2018)*

Hence, the question is: why can this market gain such success in a very short amount of time, compared to other conventional stocks or commodities, such as gold? What are cryptocurrencies about? And why does Bitcoin possess such powerful dominance? The answers lie with its origin and the whole concept of cryptocurrency – Blockchain technology.

### 2.1.2 Blockchain technology and Bitcoin's origin

The term “cryptography” refers to a discipline studying techniques to secure the information from unwanted interference or unauthorized manipulation by a third party. In human history, many civilizations tried to invent numerous methods to cipher their data. The application spreads through multiple periods from high-level security matters such as wars and politics to low-level security issues like secret love letters. In 1985, David Lee Chaum created an anonymous cryptographic electronic money – ecash – and became the first person to work with the application of cryptography technique in the most significant element of any economy

in the world, currency. From that time, the word “cryptocurrency” has been getting more and more attention from computer scientists and cryptographers. There were several other developments of this field since then. However, they did not make any remarkable changes in the financial system until 2009. This year was marked as the beginning of a worldwide phenomenon that might change the world forever. Satoshi Nakamoto – an anonymous person or a group of people, the identity remains unknown – introduced Bitcoin, a digital currency utilizing Blockchain technology.

In just 9-page white paper, they thoroughly presented the problem of current transactions and explained their exclusive solution (Nakamoto, 2009). For thousands of years since human began to involve in merchandising, a middle-man has always stayed between counterparts to ensure that one does not cheat the other. It was a simple explanation for such a complicated ecosystem. As time goes by, the so-called middle-man has evolved into government, currency, banks and many other forms. They are called “centralized” systems. They have the power and authority to manipulate the value of our deals and they take advantage of them via a commission for their services. However, still people keep wondering about the actual credibility and transparency of such centralized bodies but there are no other ways than abiding with them. Blockchain was invented to overcome that dilemma by introducing a “decentralized” system where all records are public and verified automatically by a network of tens of thousands of miners worldwide.

Due to space limitations of this thesis, detailed technical explanation is not offered but fundamental features of blockchain can be described briefly as follows:

Each blockchain represents a distinctive application of Blockchain technology. For example, Bitcoin blockchain, Ethereum blockchain, Litecoin blockchain, ... A blockchain is a sequence of multiple blocks connected closely to each other. Each block stores a few hundred transactions.

A block consists of 4 elements: transactional data, a timestamp, the hash value of the previous block and a nonce, which is a random number for verifying the hash. (Nofer et al., 2017). This design maintains the integrity of the entire blockchain through the first block, namely “genesis block”.

Participating in the network are nodes, each of which is a computer acting as a verifier for both transactions and the blocks. Another popular term for these nodes are “miners”. Miners

will be rewarded with Bitcoin or other corresponding cryptocurrencies for validating the transactions. Blockchain database is shared by all nodes in the system. Upon joining the network, each connected computer shall receive a full copy of the blockchain.

If the majority of the nodes approve, by a consensus mechanism, the transactions in a block and the block itself shall be added to the blockchain. Swanson (2015) defined this consensus mechanism as “the process in which a majority (or in some cases all) of network validators come to agreement on the state of a ledger. It is a set of rules and procedures that allows maintaining coherent set of facts between multiple participating nodes”. Once the block is put in the chain, it is almost impossible to manipulate the information. This is the most prominent element of “decentralization”. No single institution or individual has supreme authority over the system but every participant has equal influence to the system.

The impact of Blockchain technology is broad and profound. Bitcoin was merely the tip of an iceberg where thousands of applications are being created all over the world in every industry. “Smart contracts” is an outstanding example when it replaces banks and lawyer role in asset deals or it can be used to control the ownership of properties (Nofer et al., 2017). Rosamond Hutt (2016) has explained thoroughly the concept of Blockchain workflow in figure 3 in case of financial sector.

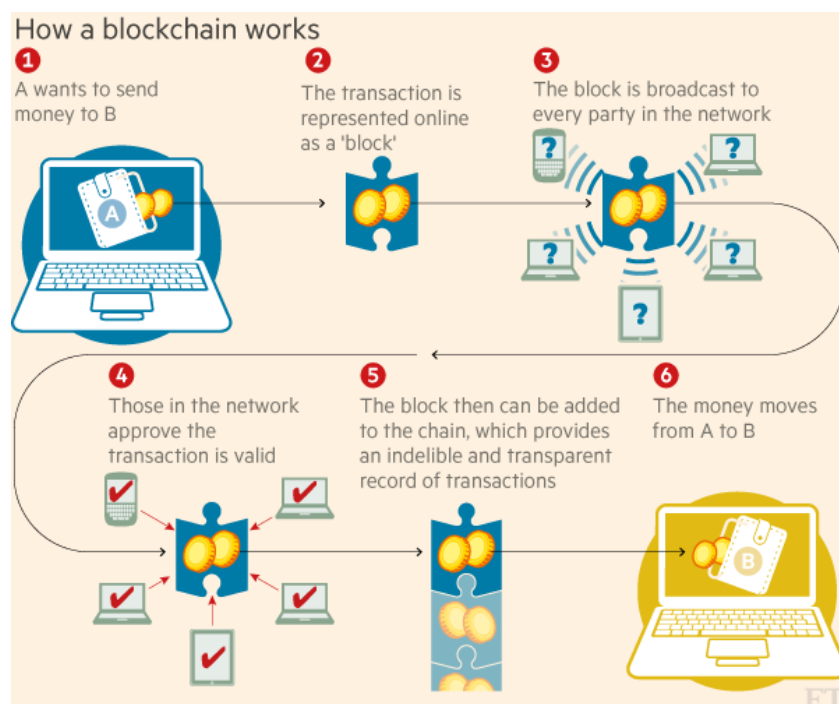


Figure 3 - Blockchain workflow  
(Hutt, 2016)

On January 09, 2009, Nakamoto Satoshi announced the release of Bitcoin v0.1, “a new electronic cash system that uses a peer-to-peer network to prevent double-spending” (Nakamoto, 2009). Blockchain technology’s first application was formulated with Bitcoin providing direct monetary transaction from one person to another. It plays the role of the initial coin in cryptocurrency, however the dominating area was just about banking and payments. Later applications found today with Blockchain have expanded further to various industries using more advanced technologies, for instance, smart contracts from Ethereum (Ethereum, 2018), digital voting from Democracy Earth (Democracy Earth, 2018), internet-of-things from Iota (Iota, 2018) and so on.

### 2.1.3 Cryptocurrency investment

In order to invest in cryptocurrency, one can pursue different paths. Especially with Bitcoin, the most reputable digital coin, there are more than one way.

- **Mining:** Initially as the Bitcoin was announced in 2009, the only path to earn bitcoin was via mining as mentioned in section 2.1.2. Miners need to invest their money into hugely powerful computers which are used to verify an exponentially growing number of transactions every day, every hour or even every second. The reward for this work is cryptocurrency itself. There are more and more individuals and institutions who are involved in such investments which sometimes leads to overloading in energy resource to support these machines. In 2018, only 9 years after Bitcoin release, electricity use for mining Bitcoin is likely to exceed all use for homes in Iceland, according to Johann Snorri Sigurbergsson – spokesman for Icelandic energy firm HS Orka (Baraniuk, 2018).
- **Gambling:** Gamblers now are able to use bitcoin for betting in online games. This is not the most common method of earning bitcoins but it is gaining popularity. The popularity originates from the nature of cryptocurrency since players are anonymous to each other, only their transactions are visible. There is no transaction fee or limitation of daily transactions. The digital feature allows a larger number of players around the globe to participate at any time they wish. Finally, they stay out of the control from authorities so some tweaks in the rule of the game are possible (Seth, 2018). Several sites offer this gambling such as satohibet, swichpoker, bitzino, etc.

- **Receiving as payment:** As cryptocurrency popularity thrives in recent years, businessmen and women began to lay an eye on bitcoin. Multiple services and products have accepted bitcoin as a payment method. The transparency of decentralized money has caused significant attention from various industries. They can benefit by cutting down the intermediate cost for middle-man. One is able to find millions of products to buy with bitcoins on promotional websites like spendabit.com, spendbitcoins.com, wheretospendbitcoins.co.uk, etc. Even though small businesses contribute more in bitcoin use proportionately, some major companies, namely Microsoft, Expedia, Overstock, Subway, have also joined the race (Nishanian, 2017).
- **Working:** Instead of ordinary wage paid with conventional currencies, one can get paid with bitcoins for their work. Types of work are varied from freelancer to full-time worker across different industries. Coinality provides comprehensive platform for jobseekers to find suitable jobs. Other platforms like BitGigs, Jobs4Bitcoins also allow jobseekers to advertise their skill and their price so employers may contact appropriate candidates instead.
- **Interest payment:** Cryptocurrency is a type of money, so it is possible to lend it at an interest rate. Lending can be done under three forms:
  - Direct lending to someone with agreed interest rate; trust plays a critical role.
  - Peer-to-peer lending using an intermediate platform such as Bitbond or BTCPOP who match lenders and borrowers at their preferred interest as well as amount of coins provided.
  - Lending coins to some websites, such as Bitcoininterest, serving as a bank for a regular interest payment. (Bajpai, 2018).
- **Trading:** Beside above methods, cryptocurrency can simply be traded for profit, similarly to stock market. The fundamental logic of trading is buy low – sell high. Meaning one should purchase the asset when its price is likely to hit the bottom, just ahead of rising again, and sell the asset when its price is like to reach the top, just ahead of dropping. It is simple but to master this dogma is an art requiring years of experience and tons of forecasting techniques. Nowadays, there are almost 200 exchanges (Cryptocurrency Market Capitalizations – 24 Hours Volume Ranking (Exchange), 2018). One can simply use conventional currency like US dollars or Euro to purchase

major coins such as Bitcoin, Ethereum, Litecoin, Bitcoin Gold. Then if they wish, they can use these major coins to exchange for other minor coins.

Although there are multiple methods to earn profit from cryptocurrency, due to the limited scope of this thesis, only Bitcoin trading shall be discussed. Bitcoin exchange possesses similarities with stock exchange as mentioned above. Several ideas and terms are identical, for instance bid and ask, bull and bear market (See Glossary) ...

## 2.2 Anchoring

### 2.2.1 Anchoring effect

Amos Tversky and Daniel Kahneman were two of the first men who studied this psychological heuristic in the 20th century. Anchoring effect is a cognitive bias reflecting the human tendency to rely on an initial impression, often quantitative, that catches their attention and influences their estimates. Once a number or a fact is given, even though they may be irrelevant to the nature of the matter, the estimates stay close to the number that was given to people – hence the image of an anchor (Kahneman, 2012, p.119). To demonstrate this phenomenon, Tvesky and Kahneman conducted an experiment where they rigged a wheel of fortune marked from 0 to 100 so that it would stop only at either 10 or 65. Then a group of students at the University of Oregon were recruited to participate in the experiment. They span the wheel and asked students to write down the number they saw, of course either 10 or 65. Afterwards, two questions were given to the students:

- Is the percentage of African nations among UN members larger or smaller than the number you just wrote?
- What is your best guess of the percentage of African nations in the UN?

Using common sense, the number students observed from the wheel obviously did not provide any useful information regarding the percentage of African nations in UN. Thus it is reasonable to expect an evenly distributed results from their answers, assuming they have no knowledge regarding this matter. However, their answers for these 2 questions proved the opposite. For those who saw 10 and 65 from the wheel, the average of their answers were 25% and 45% respectively. The existence of anchoring is confirmed.



Nevertheless, there was a debate between Tversky and Kahneman about the origin of anchoring effect which Daniel Kahneman presented clearly in the book “Thinking Fast and Slow” (2012) as follows.

### 2.2.2 Anchoring as adjustment

Amos Tversky argued that people shall base their estimates on a given anchor and make adjustments from it, so that they stay in their range of uncertainty. For example, given two questions:

- When did George Washington become the president?
- What is the boiling temperature of water at the top of Mount Everest?

As the respondents consider each of these questions, an anchor comes to their mind and they know both that it is wrong and the direction of correct answer. They know immediately that George Washington became president after 1776 and the boiling temperature of water at the top of Mount Everest is lower than 100 Celsius degrees. In their mind, they would formulate an uncertainty boundary and began to adjust down to a number which does not go outside their uncertainty boundary.

Hence, the given fact plays a role of reference point from which the brain shall make proper modification to come up with an answer that is not too distant from the reference point. The whole process reflects a mechanism of reasoning generated from accumulated experiences and complex computation in people’s minds.

### 2.2.3 Anchoring as priming effect

Priming in psychology is 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” (Trofimovich and McDonough, 2011, p.3). If one person recently heard or saw the word EAT, he is temporarily more likely to complete the word fragment SO\_P with SOUP. On the contrary, he tends to answer SOAP if he has just exposed to the word WASH. In this context, EAT primes SOUP and WASH primes SOAP. However, it is not limited to specific words but the idea can be extended to any subjects or meanings related to food or hygiene as well.

Partly disagreeing with his partner, Daniel Kahneman did not deny the existence of adjustment as a source of anchoring but he also insisted that the anchoring was triggered by priming effect. Again, two questions were used to confirm his idea:

- Was Gandhi more or less than 144 years old when he died?
- How old was Gandhi when he died?

In fact, it would seem very irrational to conclude that someone rely on 144 years old to adjust down to a reasonable number. According to Kahneman, the first question created an impression in respondent's mind that Gandhi was old when he died. In fact, this number served as a suggestion on which the mind produced a result automatically. This is perceived to be intuitive and straightforward process of the mind without careful consideration and computation as in the case of adjustments.

Nevertheless, their debate remained open until sufficient research methodology invented years after Tversky died. Eventually, both of their ideas were proven to be correct.

#### 2.2.4 Anchoring index

There is a tool to measure anchoring effect and it is called "anchoring index". To calculate this index, there should be 2 anchoring levels: high-anchor and low-anchor. For example, two questions were given to visitors at the San Francisco Exploratorium:

- Is the height of the tallest redwood more or less than 1200 feet?
- What is your best guess about the height of the tallest redwood?

In this set of questions, 1200 feet was the high-anchor. Another set of two questions were used but with the low-anchor of 180 feet instead. The difference between anchors was 1020 feet. Respondents yielded distant estimates of 844 and 282 feet for high- and low-anchor, respectively. The difference was 562 feet. Hence, the anchoring index is simply the ratio of these differences. In this case,  $562/1020$  equals 55%.

The measurement indicates if there is any anchoring at all in the considered matter and how strong anchoring effect is. 100% represents total adoption of anchors and 0% expresses definite ignorance of anchors among studied subjects.

## 2.3 Previous studies

As mentioned above, stock market possesses similarities with cryptocurrency market. Hence, the study of anchoring effect on bitcoin price can benefit from prior research in stock market as well. A number of studies on anchoring bias have been conducted on such environment.

Liao, Chou and Chiu (2013) recognized the existence of anchoring effect in foreign institutional investors' momentum behavior in Taiwan stock market. Their investment decisions were anchored to their prior ownership and the effect is stronger as prior ownership is higher. However, the anchoring effect does not lead to any improvement of momentum profitability. Sometimes, the momentum profitability suffers because of such effect. The study implies that foreign investors should rely on past experience of a certain stock only, not on how much they have previously owned, when implementing a momentum strategy. Chang, Luo, and Ren (2013) confirmed the informational and anchoring role played by the reference price of the first issued share from a firm cross-listing its share in segmented market. Kaustia, Alho and Puttonen (2008) experimented the difference in long-term stock return expectations between 213 university students and 300 Scandinavian financial market professionals. Even though students suffered stronger bias than professionals, anchoring bias was found in both groups. Verousis and Gwilym (2013) studied upstairs market of London Stock Exchange, which is based on a notional minimum price increment. They concluded that it was a resemblance of anchoring-and-adjustment effect where liquidity providers consistently buy just below the implicit minimum price increment and consistently sell just above it. From previous studies, it is certain that anchoring effect really exists in stock market and it is expected to exist also in bitcoin market. Koskinen (2013) also conducted his master thesis on the anchoring effect and came to a conclusion of its presence in UK equity market. Even professional analysts were anchored to the industry median forecast earnings per share as they made future forecasts.

Lai, Tan and Chong (2013) examined the behavior of institutional and retail investors in Bursa Malaysia during the bull and bear market situations. Their results reveal significant difference in behavior among the two groups. Particularly, institutional investors experienced significantly different price anchoring effect between bull and bear market situations whereas retail investors did not. Liao, Chou and Chiu (2013) also came up with similar conclusion in

their results. Anchoring influence on institutional investors was found to be much higher in a bear market than in a bull market.

On the other hand, there is not so much research on heuristics in bitcoin market. To the best of author's knowledge, there was one study of confirmation bias in sharing behavior of bitcoin investor by Miika Perä (2015). He found evidence proving the price change indeed manipulated the positive or negative sharing of bitcoin news. From his result, bitcoin price originates confirmation bias. Thus, one may wonder if bitcoin price had any further influence on other cognitive biases.

### 3 Hypotheses

*H1: Bitcoin prices created an anchoring effect on investors as they were placing their orders on the exchange.*

Based on previous studies, anchoring effect was confirmed to exist in normal stock market. Since bitcoin market possesses similar characteristics as stock market, author assumes this heuristic also appears in case of bitcoin investors. This phenomenon can be proved by examining the presence of a relationship between investors' bid/ask orders and bitcoin price. A time lag of 10 days is chosen as reference point to examine anchoring effect between investors' orders and Bitcoin market price.

*H2: Anchoring effect is different on askers and bidders.*

Askers and bidders are two complementary contributors in any stock-like market. Bidders create demand and askers provide supply. It would be interesting to distinguish the level of influence applied on each group by anchoring effect. That knowledge provides a general perspective on how one can utilize it to one's advantage.

*H3: The anchoring effect is different in the bull and bear market situation.*

Fluctuations in normal stock market are popular but big changes happen with lower frequency than in bitcoin market. During the second half of 2017 and first quarter of 2018, the market witnessed enormous volatility in bitcoin price. In particular, with a young market as such, no one can predict anything too far ahead or expect the effect of these tides on their investing behavior. Therefore, the research also aims to verify whether anchoring bias was recorded differently in bull and bear situations. This can be achieved by comparing correlations of investors' behavior and market price in different market situations.

## 4 Methodology

After the hypotheses were formulated, the research design needs to be constructed to act as guidelines for the whole process. As Gaudi and his partner (1995, p.26) stated, “research design is an overall plan for relating the conceptual research problem to relevant – and doable – empirical research.” Thus, it is necessary to carefully consider the design before proceeding with practicalities. Depending on the topic at hand, there are minor changes or permissible absence of some elements in a research design. However, compulsory fundamental aspects must be included in the thesis. One can name at least these five critical ingredients: purpose of the research, research strategy, data collection, data analysis, credibility and validity.

### 4.1 Purpose of the research

Researcher must define, at first, the ultimate goal for his/her work, answering the question of what kind of outcome can be expected from this study. There are three well-known classifications of research purposes including exploratory, descriptive and explanatory (Saunders et al., 2009, p.139). The short version of their definitions can be described as follows:

- Exploratory studies serve well to seek insights and approach the phenomena from a new perspective. They are more adequate to apply when the research problem is badly understood (Ghauri, Grønhaug and Kristianslund, 1995, p.28).
- Descriptive studies attempt “to portray an accurate profile of persons, events or situations” (Robson, 2002, p.59). Such studies show their effectiveness when there is a demand to have a clear vision over the phenomena.
- Explanatory studies (or causal studies) answer the causal relationships between variables (Saunders et al., 2009, p.140).

The number of studies on anchoring effect is enormous, spreading over various fields of industries including financial investment. However, according to the best knowledge of the author, no academic research had been conducted regarding anchoring bias on bitcoin investors which recently became a popular term thanks to the rocketing price change of bitcoin in particular and of cryptocurrency market in general. Consequently, this study belongs to exploratory research typology. It explores the relationship between bitcoin price and order behaviors of investors in the attempt to bring about new understanding of this market.

## 4.2 Research methods

The nature of research can be summarized in two categories, quantitative and qualitative research. As Mark Saunders and his cowriters (2009, p.151) described:

- Quantitative method is used as a synonym that implies data collection technique or data analysis procedure that generates or uses numerical data.
- Qualitative method is used as a synonym that implies data collection technique or data analysis procedure that generates or uses non-numerical data.

Researchers may select either of these research methods or both of them, called mixed method, to achieve their study objectives. In this thesis, the author decided to collect quantitative data for analysis due to the fact that all of activities on bitcoin investment are done on digital world with anonymous users. This is one of the core values offered by cryptocurrency, maintaining secrecy of its users' identity. Hence, it is possible to attain qualitative data from interviews and survey from personal sources and social networks, but the reliability is not high because there is no means to check if responders are actually make bitcoin investments. However, the order (bid/ask) on exchange definitely is representative of investor behavior. Therefore, collecting such numerical data shall have more confidence regardless of users' identity.

## 4.3 Data collection

Data can be collected via multiple research strategies, for example survey, experiments, interviews... Being different from the rest where researchers need to interact with study targets to get information, observation method allows researchers to be distant from their subjects while attaining necessary data. The name expresses literally the nature of this tool, researcher shall be an observer to watch behavior of corresponding subjects and record them for later analysis. There are two major types of observations: participant observation, which is a qualitative method utilized by participation of researcher in their subjects' lives and activities to gain and share experience with them, and structured observation, which is a quantitative method concerning with the frequency of subjects' actions (Saunders et al., 2009, p.288). In

the scope of this thesis, the interest lies only at structured observation. Alan Bryman and Emma Bell (2011, p.272) defined structured observation as follows:

*Structured observation, often also called systematic observation, is a technique in which the researcher employs, explicitly formulated rules of the observation and recording of behavior. The rules inform observers about what they should look for and how they should record behavior.*

Obviously, from the above definition the rules play a critical role in formulating the data collection procedure. In observation, one of the key decisions to make is the coding schedule to collect data (Saunders et al., p.305). One can consider several schedule themes to record data for his/her research (Bryman, 2011, p.276-p.277):

- Incidents: As something happens, record what follows from it.
- Short periods of time: Observing one subject over a short time but repeat it at structured intervals.
- Long periods of time: Observing one subject and recording continuously over a long time.
- Time sampling: The subject is observed at random time periods.

The author has chosen the observation research strategy for this thesis conducted by aggregating bids/asks and price data from a cryptocurrency exchange called Kraken. This is due to the fact that this way is more reliable to maintain objectivity of the study. However, there is no illegality in this case because all of collected information is publicly accessible via APIs (Application Programming Interface, See Glossary).

Kraken exchange provides a set of APIs that can be used to extract transactions and price data from its system at: <https://www.kraken.com/help/api>. The bids/asks data from investors for Bitcoin were collected on a continuous basis of over three months from 25 November 2017 till 03 March 2018 with the API:

*<https://api.kraken.com/0/public/Depth?pair=XXBTZEUR&count=100000000>*

The data were recorded at intervals of 30 minutes, thanks to the scheduling task feature of Spring framework, to offline database with Java language. Afterwards, they were integrated into a single file containing all numbers from the whole sampling time. The price of Bitcoin was attained with the API:



*<https://api.kraken.com/0/public/OHLC?pair=XBTEUR&interval=1440>*

Bids/asks data include the date of placing the order, offered price and amount. Price data show information of Bitcoin price in one day including the date, open, high, low, close, average. Three datasets are merged together to formulate two datasets presenting bids with corresponding Bitcoin price at the time of placing order and asks with corresponding Bitcoin price at the time of placing the order as well (See Appendix 1 for detailed coding).

## 4.4 Credibility of research findings

### 4.4.1 Reliability

Reliability refers to the extent that whether the data collection or analysis yield consistent results if similar research is to be conducted by another entity or person. It can be addressed with three questions (Easterby-Smith et al., 2009, p.109):

- Will the measures yield the same results on the other occasions?
- Will similar observations be reached by other observers?
- Is there transparency in how sense was made from the raw data?

In case of observation methods, the researcher is exposed to several particular errors in collecting data. The studied subjects might not be in equally perfect condition as they are observed, causing unnecessary noise in dataset. The time of collecting data may cause some impacts on the subject, especially in behavior research. Specific time of the day shall yield different information resulting in data that are untypical of the total time period in which the researcher is interested (Saunders et al., 2009, p.309). As mentioned in section 4.3, the schedule for observation has a critical influence on the success of data collection procedure. One might encounter difficulty in maintaining their consistency in observation schedule, known as intra-observer consistency, causing incorrect or biased data. If there are more than one person conducting the study, collision or disunion of collection timing between them shall be another obstacle to the findings credibility, known as inter-observer consistency (Bryman et al., 2011, p.279).

Ordinarily, any financial investment decisions are expected to be made with consciousness about the market dynamics as well as the potential risks involved. Cryptocurrency investments face similar expectations. Nevertheless, it is a bit different as

cryptocurrency exchanges do not operate in office hours like Wall Street but they run all day long. Investors are free to make any transactions at any time they wish as long as there are a buyer and a seller. This fact has some impact in the psychology of human mind because during different times of the day, investors might react differently with their decision. For example, John, a busy white-collar worker, may have placed an order quickly during the working hours without considering much about all details of the deal. Then John gets home, having a good dinner, drinking a cup of tea and begins to place an order. This time he has more time and is more relaxed to think thoroughly about his decision. Within the scope of this thesis, those errors are unavoidable and they could be overcome by a large amount of data in the attempt to erase the noise. On the other hand, data collection schedule has more confidence in maintaining its observation schedule. There is only one researcher conducting the research and data collection was conducted by a computer running 24/7 without any interruptions to collect data every 30 minutes. This helps prevent inconsistency of the process.

#### 4.4.2 Validity

Validity refers to the question of “whether the findings are really about what they appear to be about” (Saunders et al., 2009, p.156). There are two types of validity mentioned by Ghauri, Grønhaug and Kristianslund (1995, p.33): internal validity (refers to whether the results obtained within the study are true) and external validity (refers to whether the findings can be generalized). Particularly to observational studies, validity faces two potential threats (Bryman et al., 2011, p.280):

- Is the observation instrument administered as it is supposed to be?
- Do people change their behavior because they know they are being observed? The presence of the observer may lead to minor, sometimes major, alteration in subject reaction. As subject has abnormal behavior compared to their ordinary attitude due to this face, the study is considered to be invalid. This is known as ‘reactive effect’.

As stated above, the instrument used to collect data is absolutely digital with programmed commands acting consistently overtime. Thus attained data were unbiased and precise as all of them are kept unchanged throughout the whole data processing and analyzing. The anonymity of participants in the Bitcoin market helps trigger confidence from investors. APIs of Kraken exchange allows their data to be publicly accessible and the subjects being observed by this

study were nothing more than numerical values. Participants did not know about the presence of this research during data collection. All of those elements ensure the omission of the reactive effect from validity of research findings.

## 4.5 Data analysis

Examining the relationship between bitcoin prices and investors' orders requires two chief tools for analysis including time series analysis and correlation. Even though the presentation of each tool is separated in sub-sections, they usually interact in practice, so their appearance shall be repeated throughout the research findings in section 5 and 6. SPSS (See Glossary) is chosen to be the main statistical program in analyzing data for this thesis. Therefore, following discussed theories shall have a bias in favor of SPSS functionality and results presentation.

### 4.5.1 Time series analysis

Time series includes data points collected at a particular interval of time. It represents a sequence of random variables indexed by time that is called stochastic process or a time series process (Wooldridge, 2013, p.345). A static model of it can be observed in formula (1).

$$y_t = \beta_0 + \beta_1 z_t + u_t, t = 1, 2, \dots, n \quad (1)$$

However, if one or more variables are permitted to affect  $y$  with a time lag, formula (2) should be taken into consideration (Wooldridge, 2013, p.347). It shows a finite distributed lag model of order  $q$ .

$$y_t = \alpha_0 + \delta_0 z_t + \delta_1 z_{t-1} + \dots + \delta_q z_{t-q} + u_t \quad (2)$$

Based on above formula, the thesis ultimate goal is to examine the relationship between order price and market price via their regression coefficients of market prices with a time lag of 10 days.

The thesis applies the same method which Liao, Chou and Chiu (2013) utilized in their article. In their research, the anchoring effect can be proven to exist by regressing the changes in foreign ownership on the change in past stock returns. Similarly, for hypothesis 1, formula (3) is used to investigate the general relationship between the changes in order prices (OrdP)

and the changes in market prices (MarP) (See section 5.1 for variables notation and explanation) with anchoring effect (af).

$$OrdP_t = \alpha_0 + af_0MarP_t + af_1MarP_{t-1} + \dots + af_{30}MarP_{t-10} + u_t \quad (3)$$

For hypothesis 2, formula (4) and (5) to define anchoring bias between the changes in investors' bid prices (BidP) / ask prices (AskP) and the changes in market prices of Bitcoin (MarP).

$$BidP_t = \alpha_0 + af_0MarP_t + af_1MarP_{t-1} + \dots + af_{30}MarP_{t-10} + u_t \quad (4)$$

$$AskP_t = \alpha_0 + af_0MarP_t + af_1MarP_{t-1} + \dots + af_{30}MarP_{t-10} + u_t \quad (5)$$

Similarly, for hypothesis 3, formula (6) and (7) explore the relationship between the changes in order prices in bull (OrdBu) / bear (OrdBe) market situation and the changes in Bitcoin market price (MarP).

$$OrdPBu_t = \alpha_0 + af_0MarP_t + af_1MarP_{t-1} + \dots + af_{10}MarP_{t-10} + u_t \quad (6)$$

$$OrdPBe_t = \alpha_0 + af_0MarP_t + af_1MarP_{t-1} + \dots + af_{10}MarP_{t-10} + u_t \quad (7)$$

Nevertheless, a time series may encounter the problem of stationarity. A stationary time series process is one whose probability distributions are stable over time, meaning if any collection of random variables in the sequence is shifted ahead  $h$  time periods, the joint probability remains unchanged (Wooldridge, p.381). If a time series does not satisfy this condition, it is considered to be non-stationary and thus it would potentially lead to incorrect forecasting later in analysis. To check for stationarity, the researcher may utilize several unit root tests such as Dickey-Fuller test (Dickey et al., 1979), Phillips-Perron test (Phillips et al., 1988) or KPSS test (Kwiatkowski et al., 1992). If the time series is exposed to non-stationary threat, it should be transformed to stationary data ahead of applying any further analysis. One popular solution to such matter is differencing the data. In other words, raw dataset shall be transformed to a dataset consisting of differences between dependent variable  $y_t$  and its prior value  $y_{t-1}$  as in formula (8).

$$\Delta y_t = y_t - y_{t-1} = e_t, t = 2, 3, \dots; \quad (8)$$

In the financial sector, the price is commonly perceived as non-stationary data that needs to be transformed before analysis. Bitcoin price suffers similar challenge as well. Hence, the bids, asks and market price data are log-transformed for the sake of normalization and easy interpretation. Afterward, the differencing method shall be used to turn the dataset from non-stationary to stationary. First-order difference method creates new dataset by subtracting the value at time t-1 from the value at time t. It is noticeable that the first record of the original dataset cannot be subtracted causing differenced dataset to have one record less. In addition to adjusting the stationarity, first-order differenced data also represent the 1-day changes that are used for later regression modeling.

#### 4.5.2 Correlation coefficient

Correlation coefficient contributes greatly to identifying relationships between variables via correlation matrix. Such matrix helps investigators to spot the most important independent variables correlating to the dependent variable in the attempt to simplify the regression equation by eliminating weak correlated ones. Secondly, correlation matrix also checks multicollinearity - the correlation among independent variables. This phenomenon may distort the standard error of estimate and eventually lead to incorrect conclusions. Hence, as a rule of thumb, any relationships between two independent variables having correlation coefficient outside the range from -0.7 to +0.7 may cause multicollinearity (Mason et al., 1999, p .479).

In addition to correlation matrix, some statistical programs also automatically produce collinearity diagnostics, such as in SPSS. In the diagnostics, two values are given: Tolerance and VIF. “Tolerance” is an indicator of how much of the variability of the specified independent variable is not explained by the other independent variables in the model and is calculated using the formula 1-R squared for each variable” and “VIF” (Variance Inflation Factor) is the inverse of Tolerance value (1 divided by Tolerance) (Pallant, 2010, p.158). In case Tolerance is very small, less than 0.1, or VIF is very high, more than 10, multicollinearity exists.

It is very crucial to verify the multicollinearity between independent variables, in this case the lagged Bitcoin market price on daily basis. If multicollinearity between them is found,

the model cannot be trusted. Thus, further data preparation is required to remove such relationships among variables.

Another noteworthy mathematics tool is the calculation of the observed value of z-score ( $z_{obs}$  value). This method is used to define if the difference between correlation coefficients of two independent groups is significant. However, SPSS does not support this function, it need to be done manually (Pallant, 2010, p.140). Value  $z_{obs}$  is found via formula (9).

$$z_{obs} = \frac{z_1 - z_2}{\sqrt{\frac{1}{N_1 - 3} + \frac{1}{N_2 - 3}}} \quad (9)$$

$z_1, z_2$  standardized values of 2 correlation coefficient  $r_1, r_2$  from 2 groups (to be found with the Fisher Z-transformation table)

$N_1, N_2$  size of 2 groups

If significance level is 0.05 and  $z_{obs}$  stays in the range of  $\pm 1.96$ , correlation coefficients are not statistically significantly different. If  $z_{obs}$  remains outside of this range, correlation coefficients are statistically significantly different. This shall serve as the main tool to test hypothesis 2 and 3. In hypothesis 2,  $z_{obs}$  will determine whether significant differences in anchoring effect exists between buyers and sellers' behavior. In hypothesis 3,  $z_{obs}$  will confirm any statistically significant differences in anchoring among various market situations.

## 5 Data

### 5.1 Notation and explanation

The dataset has been processed through two stages. Firstly, raw data of bitcoin market price, bid prices and ask prices shall be weighted on daily basis to simplify the analysis. Secondly, daily mean figures are log-transformed to normalize data and 1<sup>st</sup>-order differenced to remove non-stationarity nature of them. Table 1 summarizes all variables notation. Detail explanation and calculation of variables are provided afterward.

**Table 1 - Notation**

<b>Raw Data</b>	<b>Daily Mean Data</b>	<b>1<sup>st</sup>-order differenced of log-transformed data</b>
Bid Price	Bid_Price	BidP
Ask Price	Ask_Price	AskP
Market Price	Market_Price	MarP
-	Order_Price	OrdP

*Bid Price* Raw price data of all bids placed on Kraken exchange during the data collection period. It is noticeable that bid is only an offer, no transaction has been made yet.

*Ask Price* Raw price data of all asks placed on Kraken exchange during the data collection period. It is noticeable that ask is only an ask, no transaction has been made yet.

*Market Price* Volume-weighted average price of Bitcoin on Kraken exchange. This is the ratio of total monetary value of all transactions in one certain period of time (in this case 1 day) and total number of shares (in this case coins)

traded in those transactions (Investopedia, 2018). Therefore, market price is independent of bid and ask prices.

*Bid\_Price* Bid\_Price of day D is the average of all bid prices in day D. Its value equals total monetary value of all bids placed in day D divided by the total number of bids placed in day D.

*Ask\_Price* Ask\_Price of day D is the average of all ask prices in day D. Its value equals total monetary value of all asks placed in day D divided by the total number of asks placed in day D.

*Market\_Price* Since raw data of market price were collected as a single value for everyday already, average value of market price for one day equals to itself. Hence, Market\_Price equals to Market Price.

*Order\_Price* Order\_Price of day D is the average of all bid and ask prices in day D. Its value equals total monetary value of all bids and asks placed in day D divided by the total number of bids and asks placed in day D.

*BidP* The changes in  $\log(\text{Bid\_Price})$ .  

$$\text{BidP}_{t-1:t} = \Delta \log(\text{Bid\_Price})_{t-1:t} = \log(\text{Bid\_Price})_t - \log(\text{Bid\_Price})_{t-1}$$

*AskP* The changes in  $\log(\text{Ask\_Price})$ .  

$$\text{AskP}_{t-1:t} = \Delta \log(\text{Ask\_Price})_{t-1:t} = \log(\text{Ask\_Price})_t - \log(\text{Ask\_Price})_{t-1}$$

*MarP* The changes in  $\log(\text{Market\_Price})$ .  

$$\text{MarP}_{t-1:t} = \Delta \log(\text{Market\_Price})_{t-1:t} = \log(\text{Market\_Price})_t - \log(\text{Market\_Price})_{t-1}$$



In the regression model, MarP is denoted as MarP\_0, MarP\_1, MarP\_2, ..., MarP\_10 representing market price 1-day change from the day the order was made (MarP<sub>0</sub>) back to the market price 1-day change of prior 10 days (MarP<sub>10</sub>).

*OrdP* The changes in  $\log(\text{Order\_Price})$ .

$$\text{OrdP}_{t-1:t} = \Delta \log(\text{Ord\_Price})_{t-1:t} = \log(\text{Ord\_Price})_t - \log(\text{Ord\_Price})_{t-1}$$

## 5.2 Descriptive Statistics

Table 2 - Descriptive Statistics of Raw Data

	N	Minimum	Maximum	Mean	Std. Deviation
<b>Ask Price</b>	317999	4746.800	29000.000	9991.393	2667.21214
<b>Bid Price</b>	379861	4094.400	16282.200	9367.689	2407.315121
<b>Market Price</b>	99	5449.258	15922.429	10148.969	2485.381656

As stated in section 4.3, the data were collected over a period exceeding 3 months, 99 days to be precise. Table 1 summarizes descriptive statistics for ask price, bid price, and Bitcoin price on daily basis. Throughout the period, Bitcoin market has witnessed both significant rises and declines with the highest value of 15.922 € and lowest of 5.449 €. Similarly, ask price and bid price vary from 4.746 € to 29.000 € and 4.094 € to 16.282 € respectively. Three variables' means and standard deviations are not too different from each other.

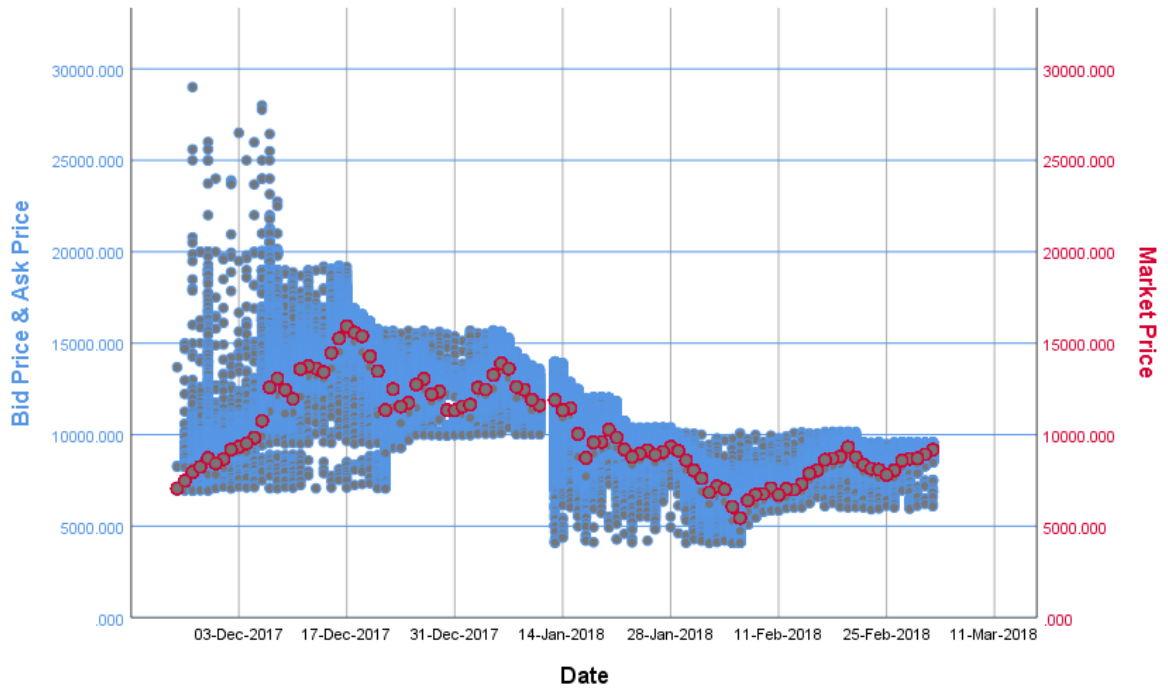


Figure 4 - Bid price, ask price and Bitcoin market price

Figure 4 exhibits bid prices and ask prices (marked with blue color) in comparison with Bitcoin market price fluctuation (marked with red color). It should be noted that in the raw dataset, several bid/ask orders were over/under the market price of Bitcoin, respectively. This is due to the fact that the market price is the average of daily price fluctuation, thus some bid orders might follow the high price of the day or some ask orders followed the low price of the day.

### 5.3 Stationarity test of raw data

To utilize the model in section 4.5.1, daily average of all bid and ask prices were computed and abbreviated as Order\_Price. Along with Bitcoin market price, abbreviated as Market\_Price, the regression can be processed simpler. Figure 5 presents the new formulated data in the relationship with market price. Later in the analysis process, daily average bid prices (Bid\_Price) and daily average ask prices (Ask\_Price) will be computed as well to serve in testing hypothesis 2.

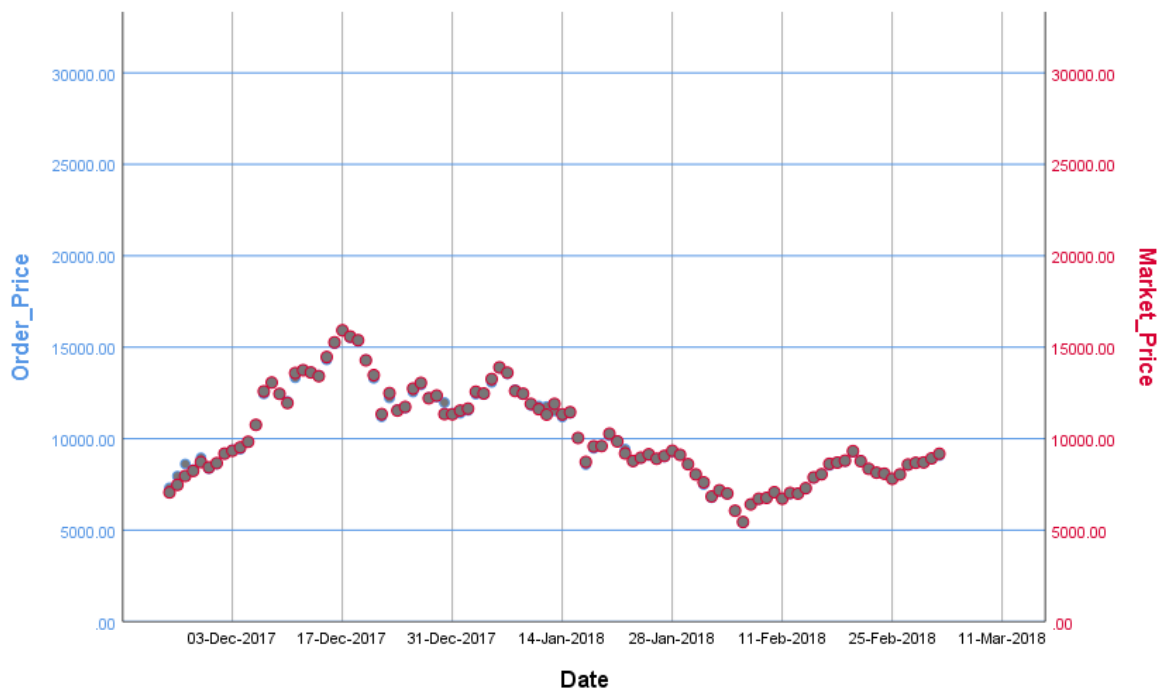


Figure 5 - Daily average order price (Ord\_Price) and market price (Market\_Price)

The theory has implied the importance of stationary characteristics of data in time series analysis. Hence, all four series of Market\_Price, Order\_Price, Bid\_Price and Ask\_Price need to be examined to confirm their fit for time series analysis. Author uses 3 statistical tools to check the stationary status of Market\_Price, Order\_Price, Bid\_Price and Ask\_Price. The results are presented in table 3.

Table 3 - Stationary test of raw data

		Market_Price	Order_Price	Bid_Price	Ask_Price
<b>Dickey-Fuller</b>	Tau (Observed value)	-2,602	-2,515	-2,573	-2,553
	Tau (Critical value)	-3,410	-3,410	-3,410	-3,410
	p-value (one-tailed)	0,268	0,306	0,280	0,289
	alpha	0,05	0,05	0,05	0,05
<b>Phillips-Perron</b>	Tau (Observed value)	-0,104	-0,135	-0,140	-0,427
	Tau (Critical value)	-1,944	-1,944	-1,944	-1,944
	p-value (one-tailed)	0,645	0,635	0,633	0,527

	alpha	0,05	0,05	0,05	0,05
<b>KPSS</b>	Eta (Observed value)	1,583	1,636	1,526	1,841
	Eta (Critical value)	0,451	0,451	0,451	0,451
	p-value (one-tailed)	< 0,0001	< 0,0001	< 0,0001	< 0,0001
	alpha	0,05	0,05	0,05	0,05

The null hypothesis of Dickey-Fuller and Phillips-Perron tests insists that there is a unit root for the series, meaning data are not stationary. In case of all four series from daily average data, both tests produce p-values greater than 0.05 confirming the acceptance of null hypothesis. On the contrary, KPSS test's null hypothesis states that the series is stationary. P-value produced by KPSS is significantly smaller than 0.05 telling that the series are non-stationary.

Consequently, transformation is required in this case to normalize data for time series analysis. By applying log transformation and first-order differencing method discussed in section 4.5.1, four series of Market\_Price, Order\_Price, Bid\_Price and Ask\_Price data were transformed to four series of MarP, OrdP, BidP and AskP data. Figure 6 shows the results after transformation of Market\_Price and Order\_Price.

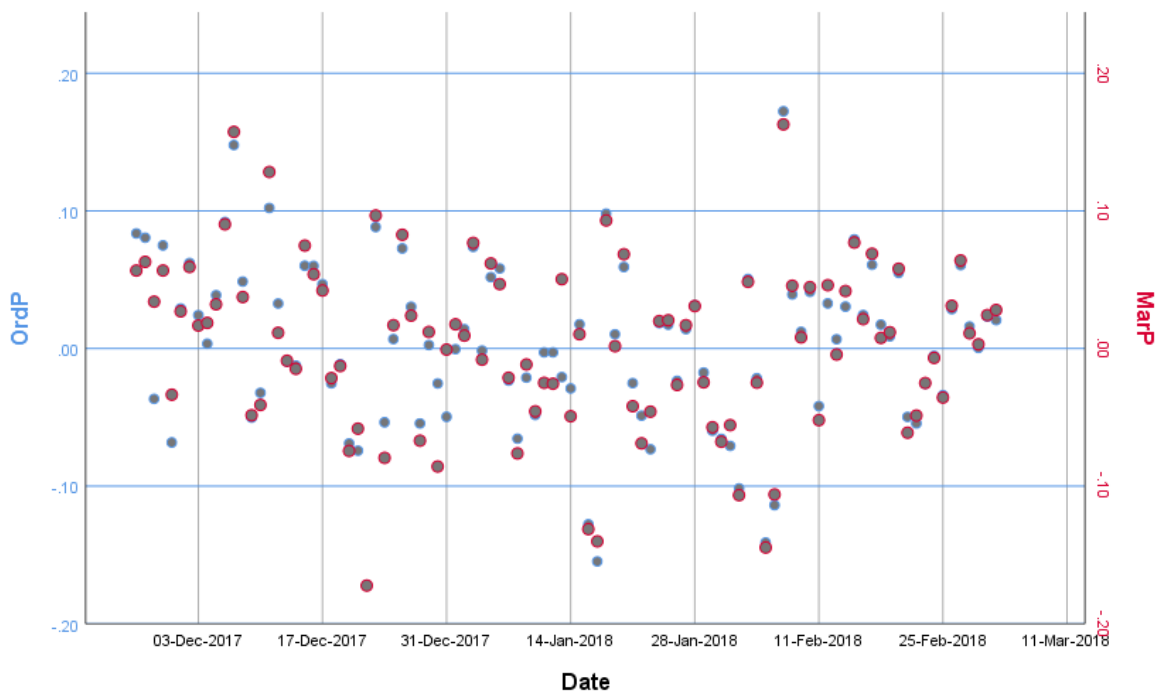


Figure 6 - Data after log-transformation and 1<sup>st</sup>-order difference

**Table 4 - Stationary test of transformed data**

		<b>MarP</b>	<b>OrdP</b>	<b>BidP</b>	<b>AskP</b>
<b>Dickey-Fuller</b>	Tau (Observed value)	-3,873	-4,059	-4,086	-4,200
	Tau (Critical value)	-3,421	-3,421	-3,421	-3,421
	p-value (one-tailed)	0,014	0,009	0,008	0,006
	alpha	0,05	0,05	0,05	0,05
<b>Phillips-Perron</b>	Tau (Observed value)	-8,468	-8,206	-8,448	-8,601
	Tau (Critical value)	-1,944	-1,944	-1,944	-1,944
	p-value (one-tailed)	< 0,0001	< 0,0001	< 0,0001	< 0,0001
	alpha	0,05	0,05	0,05	0,05
<b>KPSS</b>	Eta (Observed value)	0,289	0,269	0,238	0,143
	Eta (Critical value)	0,451	0,451	0,451	0,451
	p-value (one-tailed)	0,149	0,169	0,211	0,435
	alpha	0,05	0,05	0,05	0,05

All unit root test results validate the non-stationary status of four series MarP, OrdP, BidP and AskP. As shown in table 4, p-values of Dickey-Fuller and Phillips-Perron tests now are much smaller than 0.05 and KPSS's p-value exceeds 0.05. They verify the stationarity of the new dataset which is ready to be used for further time series analysis.

## 6 Empirical results

### 6.1 Order prices and Bitcoin market prices

With the new transformed dataset, regression analysis is able to proceed in the attempt to investigate the relationship between the changes in order price (OrdP) and the changes in market price (MarP) based on formula (3) in section 4.5.1. The dependent variable in this case is OrdP and independent variables are 1-day changes in market price starting from the day of order placement, denoted as MarP\_0, back to 10 days before, denoted as MarP\_1, MarP\_2, ..., MarP\_10.

Firstly, the multicollinearity of independent variables should be checked. Models are built under the form of finite distributed lag of order ten. Meaning there would be 11 independent variables standing for 1-day changes in market value of Bitcoin from the day the order was made back to prior 10 days. Table 5 expresses clearly the Pearson coefficient correlations between the 11 independent variables and no absolute values exceed 0.7 implying

the absence of multicollinearity as stated in section 4.5.2. Further evidence can be found in coefficients table, table 7, that all collinearity tolerances are greater than 0.1 and VIFs are smaller than 10. Hence, it can be confirmed that there is no significant multicollinearity between independent variables of the models.

**Table 5 - Pearson correlation of OrdP and MarP**

	OrdP	MarP_0	MarP_1	MarP_2	MarP_3	MarP_4	MarP_5	MarP_6	MarP_7	MarP_8	MarP_9	MarP_10
OrdP	1,000											
MarP_0	0,962	1,000										
MarP_1	0,214	0,147	1,000									
MarP_2	-0,015	0,015	0,144	1,000								
MarP_3	0,007	0,002	0,016	0,147	1,000							
MarP_4	0,034	0,037	0,004	0,014	0,146	1,000						
MarP_5	0,011	0,030	0,035	-0,002	0,013	0,146	1,000					
MarP_6	0,054	0,050	0,027	0,032	-0,003	0,013	0,143	1,000				
MarP_7	0,012	-0,003	0,056	0,032	0,032	-0,003	0,020	0,147	1,000			
MarP_8	0,042	0,090	-0,006	0,054	0,033	0,032	-0,002	0,018	0,145	1,000		
MarP_9	0,128	0,095	0,095	-0,003	0,052	0,034	0,038	0,005	0,017	0,142	1,000	
MarP_10	0,130	0,137	0,101	0,097	-0,005	0,054	0,044	0,047	0,001	0,012	0,144	1,000

**Table 6 - OrdP - MarP Regression model summary**

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.968 <sup>a</sup>	.936	.928	0,01635	.936	114,864	11	86	0,000

**Table 7 - OrdP - MarP Regression Coefficients**

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95,0% Confidence Interval for B		Collinearity Statistics	
		B	Std. Error	Beta			Lower Bound	Upper Bound	Tolerance	VIF
1	(Constant)	0,000	0,002		-0,252	0,802	-0,004	0,003		
	MarP_0	0,940	0,028	0,954	34,129	0,000	0,885	0,995	0,949	1,054
	MarP_1	0,074	0,028	0,076	2,698	0,008	0,020	0,129	0,943	1,061
	MarP_2	-0,038	0,028	-0,039	-1,388	0,169	-0,093	0,017	0,946	1,057
	MarP_3	0,009	0,027	0,009	0,317	0,752	-0,046	0,063	0,953	1,049
	MarP_4	0,001	0,027	0,002	0,054	0,957	-0,053	0,056	0,954	1,049
	MarP_5	-0,022	0,028	-0,022	-0,808	0,421	-0,077	0,033	0,956	1,046
	MarP_6	0,008	0,028	0,008	0,278	0,781	-0,047	0,063	0,955	1,048
	MarP_7	0,018	0,028	0,018	0,645	0,520	-0,037	0,073	0,953	1,049
	MarP_8	-0,050	0,028	-0,050	-1,786	0,078	-0,105	0,006	0,948	1,055
	MarP_9	0,037	0,028	0,038	1,348	0,181	-0,018	0,093	0,945	1,058
	MarP_10	-0,009	0,028	-0,009	-0,328	0,744	-0,064	0,046	0,946	1,057

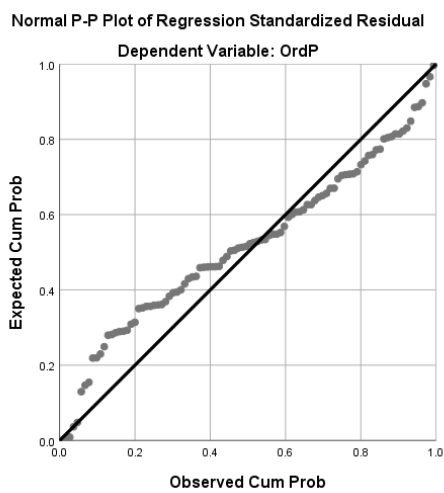


Figure 7 – OrdP – MarP P-P plot

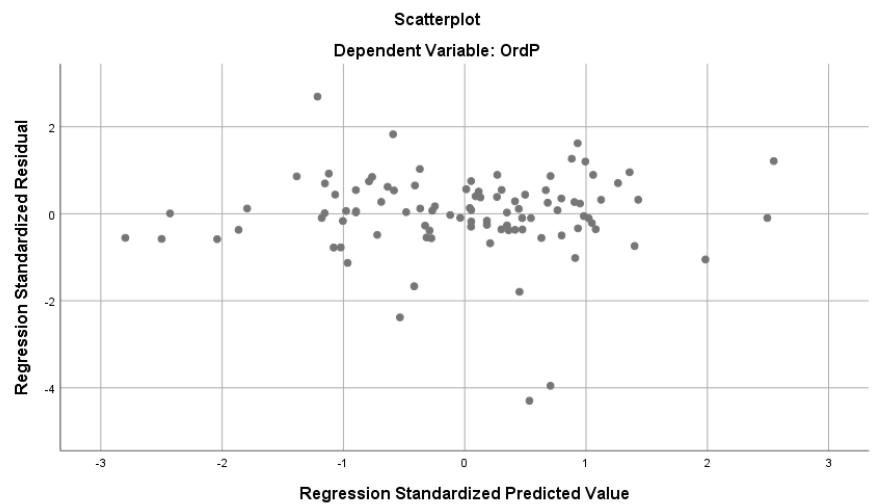


Figure 8 - OrdP – MarP Scatterplot

Table 6, 7 and figure 7, 8 report important parameters for regression model expressing the relationship between OrdP and MarP. High R square of 0.936 in table 6 confirms the great fitness of formulated model to predict the data.

Coefficient of each independent variable is shown in table 7. However, none of them had significant contribution to the model except for the change in market price on the day of order placement (MarP\_0) and the change in market price on previous day (MarP\_1). Their significance value of 0.000 and 0.008, respectively, were smaller than 0.05 (the analysis use confidence level of 95%). Nevertheless, the influence to regression model has a huge difference between them. The result exhibits clearly that the change in Bitcoin price at t (MarP\_0) contributed greatly to the equation with the Standardized Coefficient Beta of 0.954, nearly to the perfect level of 1.0. Meanwhile, the change in market price at t-1 (MarP\_1) had significantly less impact with the Beta of 0.076. Other independent variables did not make any significant contribution. It can be interpreted as follows: the change in order price would increase by 0.954% if the change in market price increases by 1% over the past day.

The P-P plot in figure 7 shows that standardized residual values aligned closely to the diagonal line. Meaning there was no serious deviation from the normality. Scatterplot in figure 8 presents data points centered around the mark of 0 implying no violation to the model assumption (Pallant, 2010, p.158 – 159).

In conclusion, the regression analysis has proven the existence of a strong relationship between the changes in order price and the changes in Bitcoin market price. The strongest impact came from the change in market price of the day when investor places the order and the change in market price of one day before has second strongest influence. This implies a fact that investors altered their order prices accordingly to the current change in market price. Anchoring effect was proven to exist in this case. Hypothesis 1 has been verified.

## 6.2 Bid prices and ask prices

The anchoring bias has been confirmed to endure between Bitcoin price change and investors' behaviors. Next question is whether this bias has formed different influences on bidding and asking decisions. Formula (4) and (5) from section 4.5.1 were used to execute



regression analysis on two pairs of relationship: BidP – MarP and AskP – MarP (their results are to be found in Appendix B and Appendix C, respectively).

The output has confirmed a strong connection between dependent variables BidP and AskP on independent variable MarP\_0, other time lags did not show any strong influence on bid and ask orders. In case of BidP, MarP\_0 made significant contribution to its regression model with the Beta of 0.952. The corresponding figure in case of AskP was 0.880. Multicollinearity as well as deviation from normality or violation of model assumption did not exist in the data (similar logic as in section 6.1).

Since both changes in ask and bid price have a relationship to the market price change, the strength of these relationships can be examined via their correlations. Table 7 aggregates correlation coefficients from regression analyses along with corresponding z-score of Fisher. The observed z scores were computed based on the following equation adopted from formula (9) in section 4.5.2.

$$z_{obs} = \frac{z_{Bid} - z_{Ask}}{\sqrt{\frac{1}{99 - 3} + \frac{1}{99 - 3}}}$$

**Table 8 - Bid/Ask Pearson correlation coefficients**

	<b>BidP</b>	<b>AskP</b>	<b>ZBid</b>	<b>ZAsk</b>	<b>ZObs</b>
<b>MarP_0</b>	0,956	0,885	1,893	1,397	3,439
<b>MarP_1</b>	0,165	0,172	0,167	0,174	-0,047
<b>MarP_2</b>	0,009	-0,012	0,009	-0,012	0,145
<b>MarP_3</b>	-0,022	0,024	-0,022	0,024	-0,319
<b>MarP_4</b>	0,004	0,071	0,004	0,071	-0,468
<b>MarP_5</b>	0,016	0,025	0,016	0,025	-0,067
<b>MarP_6</b>	0,087	-0,001	0,087	-0,001	0,610
<b>MarP_7</b>	-0,043	0,021	-0,043	0,021	-0,444
<b>MarP_8</b>	0,113	0,060	0,113	0,060	0,366
<b>MarP_9</b>	0,111	0,068	0,112	0,068	0,305
<b>MarP_10</b>	0,083	0,148	0,084	0,149	-0,454

If  $z_{obs}$  falls in the range between -1.96 and 1.96, it can be concluded that there is no statistically significant difference between correlation coefficients. The series of  $z_{obs}$  in Table 8 has only one value stay outside of this range which is the  $z_{obs}$  of MarP\_0, remaining values

fell between the boundaries. Hence, BidP and AskP only had statistically different correlation coefficients at the MarP\_0. At other lagged periods, they were quite similar. However, because the MarP\_0, as mentioned above, had the most significant and unique contribution to regression equation, it is reasonable to conclude that there were differences between correlation of BidP and AskP with MarP.

The positive value of  $z_{obs}$  at MarP\_0 (3.439) also implies that change in market price had more influence on investors' decision as they placed bid orders than ask orders. Consequently, hypothesis 2 is accepted.

### 6.3 Bull and bear market

In order to test hypothesis 3, regression analyses were conducted on OrdP and MarP in different market situations using formula (6) and (7). Figure 7 demonstrates the fluctuation of Bitcoin price throughout the period from 25 November 2017 till 11 March 2018. The author decided to select two periods where bull and bear market situations exhibited clearest.

The bull situation can be observed from 25 November 2017 till 17 December 2017 where Bitcoin price reached its peak. This period lasted for 22 days witnessing an uptrend market. The bear situation can be observed from 6 January 2018 till 6 February 2018 where Bitcoin price hit its rock bottom. The period lasted for 32 days with a downtrend in the market.

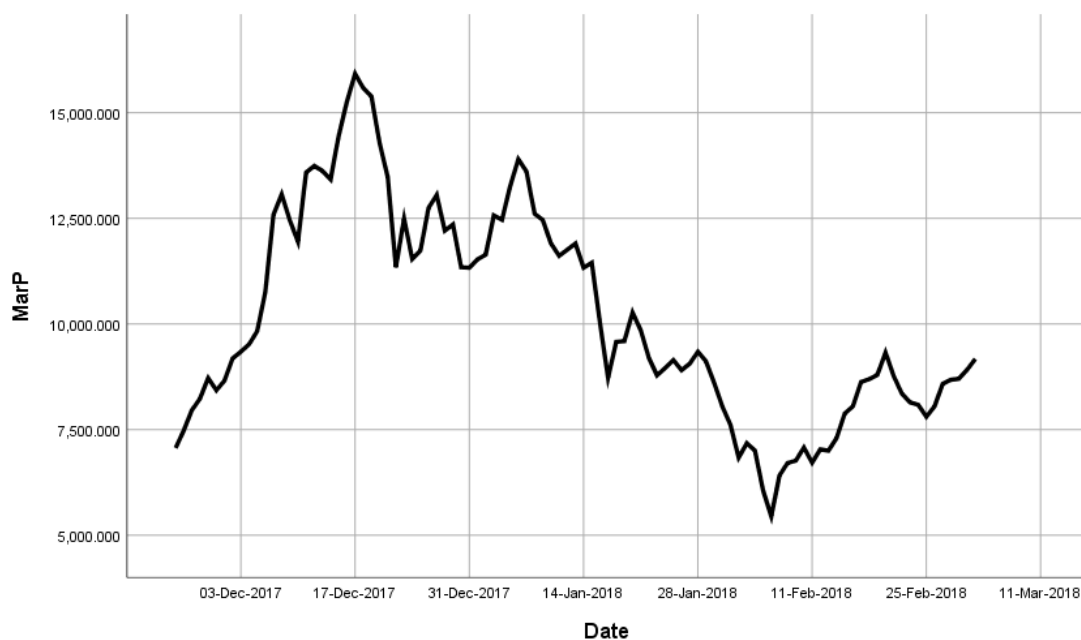


Figure 7 - Bitcoin market price fluctuation from 25 November 2017 to 11 March 2018

Regression analyses for data in bull and bear market had produced outputs as shown in Appendix D and E, respectively. The only significant independent variable to both regression models was MarP\_0. In bull market, it contributed greatly with the Beta of 0.904 while this number in bear market was 0.924. The two models had great fitness with incredibly high R square values. Multicollinearity, deviation from normality and violation of model assumption were not found in this case. Pearson’s correlation coefficients of OrdP and MarP in bull and bear market situations are presented in table 9, along with  $z_{obs}$  obtained from following formula.

$$z_{obs} = \frac{z_{Bull} - z_{Bear}}{\sqrt{\frac{1}{22 - 3} + \frac{1}{32 - 3}}}$$

**Table 9 - Bull/Bear market correlation coefficients**

	OrdPBu	OrdPBe	ZBull	ZBear	ZObs
MarP_0	0,919	0,959	1,585	1,935	-1,186
MarP_1	0,131	0,209	0,132	0,212	-0,271
MarP_2	-0,459	-0,156	-0,496	-0,157	-1,148
MarP_3	-0,384	-0,127	-0,405	-0,127	-0,940
MarP_4	0,187	-0,134	0,189	-0,134	1,096
MarP_5	0,196	0,097	0,199	0,097	0,343
MarP_6	-0,120	0,247	-0,121	0,252	-1,262
MarP_7	-0,326	0,097	-0,339	0,097	-1,477
MarP_8	-0,077	-0,072	-0,077	-0,072	-0,016
MarP_9	0,368	0,085	0,386	0,085	1,019
MarP_10	0,349	-0,065	0,364	-0,065	1,452

It can be seen from Table 9 that all observed z-scores fell between the range of -1.96 and 1.96. This implies no significantly different correlation, of the change in order price and the change in Bitcoin price, was found between the two market situations. Consequently, hypothesis 3 is rejected.

## 7 Conclusion

Statistical analyses from section 6 have verified the existence of anchoring bias in the dynamic market of Bitcoin. Investors in the study were heavily anchored as they would make changes to their bid/ask price in correspondence to the current change in Bitcoin price. However, in this particular case, anchoring as adjustment seems to be a more reasonable explanation over the phenomenon than anchoring as priming effect. When investors decided to place an order to buy or sell their coin(s), they already had access to Bitcoin price change data in the past, which were publicly published on many online sources, but they decided to rely on the price change at the moment of ordering. This expresses the uncertainty of investors in judging future value of Bitcoin. Hence, priming effect was not found from Bitcoin price because it did not cause critical impression on people's minds about whether market would rise or collapse. It rather exhibits the fact that people tend to anchor on the current Bitcoin price change to make appropriate adjustments, up or down, within a confident boundary to their selling price or buying price, respectively. Evidently, this conclusion is an echo to prior studies as it confirms the presence of anchoring bias in investors' trading decisions in stock market. The results complement Liao, Chou and Chiu (2013) research by using the same methodology with different variables. Instead of examining the change in ownership and the change in past stock returns, this thesis confirms a positive relationship between the change in order price and the change in market price. However, similar outcomes are found in both studies. Furthermore, previous studies are also complemented with a different perspective as the thesis examines a realized value, Bitcoin market price, with unrealized values, bids and asks.

Approval of hypothesis 2 has confirmed a statistically significant difference among anchoring bias impact to bidding and asking decisions. Anchoring influence was found greater in bidding actions than asking actions. The explanation for this phenomenon can be found in the desire to join in this potential market of investors. Buyers would place a bid closer to the price because they did not want to bargain an opportunity to purchase Bitcoin with a lower price. Meanwhile, sellers had more flexibility in pricing their assets on the exchange because they acknowledged the high market demand.

Rejection of hypothesis 3 has extended the study of bull and bear anchoring bias to another dimension, cryptocurrency. This result aligns with research done by Lai, Tan & Chong (2013). They found that anchoring impact was not different between bull and bear markets in

retail investors. Retail investors in this case were identified using the amount of Bitcoins in every bid and ask orders. The institutional investors are expected to make big orders with large amount of Bitcoins. Even though there is no clear standard to define which amount is considered to be large, more than 90% of orders were placed with less than 10 Bitcoins in each. This can be a considerable reference point to expect subjects of this study to be ordinary people, not institutional investors.

Cryptocurrency investors in general, and Bitcoin investors in particular, should be careful with this heuristic when evaluating their bid and ask values on cryptocurrency exchange. It can draw them away from correct prediction of future value, leading to underpriced selling or overpriced buying. Eventually, investors must suffer from their bad decisions the huge opportunity costs, or even realized damages. On the other hand, if one can acknowledge this bias and takes advantage of it, better trading performance and greater profit are promised. For example, a seller might place an ask order at a much higher price than the current price with great confidence if he/she knew, from media or research, that Bitcoin price would double in the near future. Because most of the buyers are anchored to the current price, the chance of having no bid matched with his/her ask order is very low.

Nevertheless, there are still some limitations in this research and it can be improved or expanded further in future. The study took into consideration only changes in Bitcoin price as a predictor when analyzing anchoring effect. Other influential factors to traders' behaviors can be added as control variables to the regression model for better interpretation of the phenomenon. Identity and demographics of subjects in this study remain unknown due to previously mentioned reasons. If one may conduct interviews with credible investors, it can be another interesting research topic to explore. For example, whether anchoring effect is stronger in young and digitally oriented investors with less trading experience or it is stronger in older investors with more experience but limited access to modern analytic tools. Besides, anchoring is only a fraction of the bigger picture of psychological heuristics. Studies on other biases in this market is promising due to the young but dynamic economy of cryptocurrency, a fertilized land with enormous potential application in every aspect of human life.

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## Appendix A: Java code for data collection

```
public class RunMeTask2 {
    public void printMe() {
        try {
            Date now = new Date();
            String datenow = new SimpleDateFormat("MM/dd/yyyy
HH:mm:ss").format(now);
            final String parentPath = "C:\\Users\\Chu
Lung\\Desktop\\CryptoData";
            System.out.println("Run price check at: " + datenow);
            final String apiUrl =
"https://api.kraken.com/0/public/OHLC?pair=XBTEUR&interval=1440";
            URL url = new URL(apiUrl + "&since=0");
            HttpURLConnection conn = (HttpURLConnection)
url.openConnection();
            conn.setRequestMethod("GET");
            conn.setRequestProperty("Accept", "application/json");

            BufferedReader br = new BufferedReader(new
InputStreamReader((conn.getInputStream())));

            StringBuilder sb = new StringBuilder();
            String output;
            System.out.println("Output from Server .... \n");
            while ((output = br.readLine()) != null) {
                sb.append(output);
            }

            String jsonString = sb.toString();
            JSONObject obj;
            List<Entry> listEntry = new ArrayList<Entry>();

            try {
                obj = new JSONObject(jsonString);
                final JSONArray result =
obj.getJSONObject("result").getJSONArray("XXBTZEUR");
```

```
for (int i = 0; i < result.length(); i++) {
    JSONArray record = result.getJSONArray(i);

    Long time = record.getLong(0);
    Double open = record.getDouble(1);
    Double high = record.getDouble(2);
    Double low = record.getDouble(3);
    Double close = record.getDouble(4);
    Double vwap = record.getDouble(5);
    Double volume = record.getDouble(6);
    Double count = record.getDouble(7);

    Entry entry = new Entry(time, open, high, low,
close, vwap, volume, count);
    listEntry.add(entry);
}

File directory = new File(parentPath);
if(! directory.exists()) directory.mkdirs();

File file = new File(directory + "\\checkPrice.txt");

file.createNewFile();

BufferedWriter writer = new BufferedWriter(new
FileWriter(file));

for (Entry entry : listEntry) {
    writer.write(new SimpleDateFormat("MM/dd/yyyy
HH:mm:ss").format(new Date(entry.getDate() * 1000L)));
    writer.write(",");
    writer.write(entry.getOpen().toString());
    writer.write(",");
    writer.write(entry.getHigh().toString());
    writer.write(",");
    writer.write(entry.getLow().toString());
```

```
        writer.write(",");
        writer.write(entry.getClose().toString());
        writer.write(",");
        writer.write(entry.getVwap().toString());
        writer.write(",");
        writer.write(entry.getVolume().toString());
        writer.write(",");
        writer.write(entry.getCount().toString());
        writer.write(",");
        writer.newLine();
    }
    writer.close();

} catch (JSONException e) {
    // TODO Auto-generated catch block
    e.printStackTrace();
}

conn.disconnect();

} catch (MalformedURLException e) {

    e.printStackTrace();

} catch (IOException e) {

    e.printStackTrace();

}

}

class Entry {
    Long date;
    Double open;
    Double high;
    Double low;
    Double close;
```

```
Double vwap;
Double volume;
Double count;

    public Entry(Long date, double open, double high, double low, double
close, double vwap, double volume, double count) {
        this.date = date;
        this.open = open;
        this.high = high;
        this.low = low;
        this.close = close;
        this.vwap = vwap;
        this.volume = volume;
        this.count = count;
    }

    public Long getDate() {
        return date;
    }

    public void setDate(Long date) {
        this.date = date;
    }

    public Double getOpen() {
        return open;
    }

    public void setOpen(Double open) {
        this.open = open;
    }

    public Double getHigh() {
        return high;
    }

    public void setHigh(Double high) {
        this.high = high;
    }
```

---

```
    }

    public Double getLow() {
        return low;
    }

    public void setLow(Double low) {
        this.low = low;
    }

    public Double getClose() {
        return close;
    }

    public void setClose(Double close) {
        this.close = close;
    }

    public Double getVwap() {
        return vwap;
    }

    public void setVwap(Double vwap) {
        this.vwap = vwap;
    }

    public Double getVolume() {
        return volume;
    }

    public void setVolume(Double volume) {
        this.volume = volume;
    }

    public Double getCount() {
        return count;
    }
}
```

```
        public void setCount(Double count) {  
            this.count = count;  
        }  
    }  
}
```

## Appendix B: BidP - MarP regression model

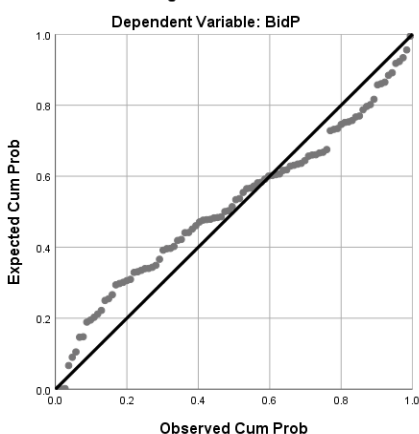
### Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.961 <sup>a</sup>	0,924	0,914	0,01940	0,924	94,437	11	86	0,000

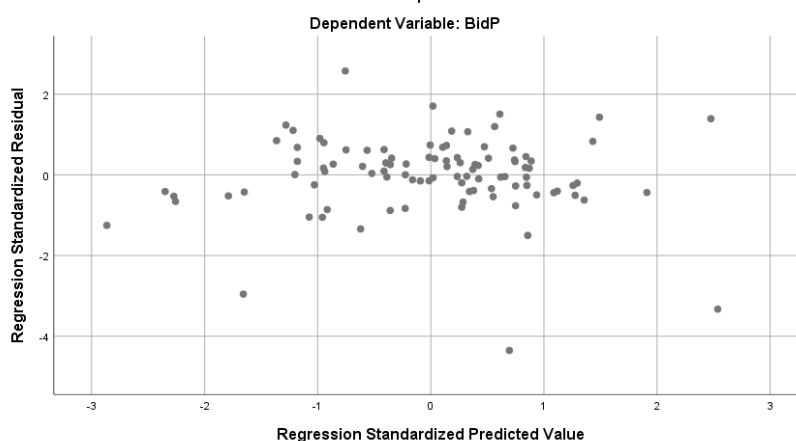
### Coefficients

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	99,0% Confidence Interval for B		Collinearity Statistics	
	B	Std. Error	Beta			Lower Bound	Upper Bound	Tolerance	VIF
1 (Constant)	0,000	0,002		-0,051	0,960	-0,004	0,004		
MarP_0	1,017	0,033	0,952	31,104	0,000	0,952	1,082	0,949	1,054
MarP_1	0,032	0,033	0,030	0,984	0,328	-0,033	0,097	0,942	1,061
MarP_2	-0,003	0,033	-0,003	-0,098	0,922	-0,068	0,062	0,945	1,058
MarP_3	-0,022	0,033	-0,021	-0,674	0,502	-0,087	0,043	0,953	1,049
MarP_4	-0,029	0,033	-0,027	-0,875	0,384	-0,093	0,036	0,954	1,049
MarP_5	-0,015	0,033	-0,014	-0,459	0,648	-0,080	0,050	0,956	1,046
MarP_6	0,054	0,033	0,050	1,648	0,103	-0,011	0,119	0,955	1,048
MarP_7	-0,057	0,033	-0,053	-1,730	0,087	-0,122	0,008	0,954	1,049
MarP_8	0,035	0,033	0,033	1,066	0,289	-0,030	0,101	0,948	1,055
MarP_9	0,026	0,033	0,024	0,783	0,436	-0,040	0,091	0,945	1,058
MarP_10	-0,058	0,033	-0,054	-1,768	0,081	-0,124	0,007	0,946	1,057

Normal P-P Plot of Regression Standardized Residual



Scatterplot





## Appendix C: AskP - MarP regression model

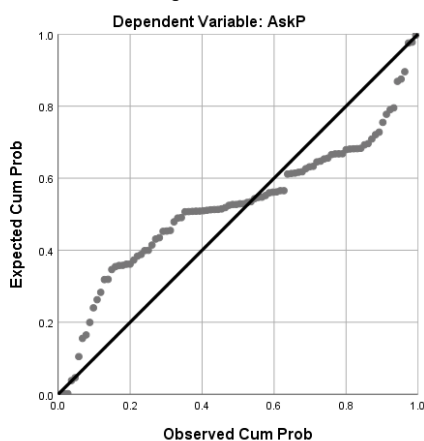
### Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.890a	0,792	0,765	0,02872	0,792	29,777	11	86	0,000

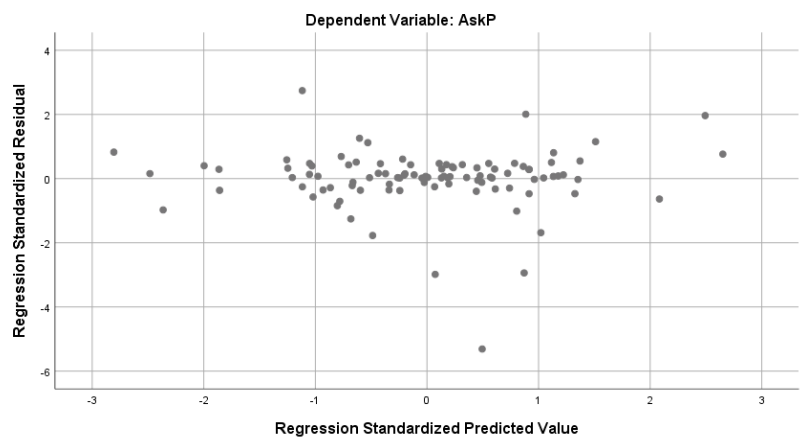
### Coefficients

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	99,0% Confidence Interval for B		Collinearity Statistics	
	B	Std. Error	Beta			Lower Bound	Upper Bound	Tolerance	VIF
1 (Constant)	-0,003	0,003		-1,138	0,258	-0,009	0,002		
MarP_0	0,843	0,048	0,880	17,424	0,000	0,747	0,939	0,949	1,054
MarP_1	0,044	0,049	0,046	0,901	0,370	-0,053	0,140	0,942	1,061
MarP_2	-0,036	0,049	-0,037	-0,739	0,462	-0,132	0,061	0,945	1,058
MarP_3	0,022	0,048	0,023	0,451	0,653	-0,074	0,118	0,953	1,049
MarP_4	0,035	0,048	0,036	0,715	0,477	-0,061	0,130	0,954	1,049
MarP_5	-0,002	0,048	-0,002	-0,035	0,972	-0,098	0,095	0,956	1,046
MarP_6	-0,049	0,048	-0,051	-1,015	0,313	-0,146	0,047	0,955	1,048
MarP_7	0,032	0,049	0,033	0,656	0,514	-0,065	0,128	0,954	1,049
MarP_8	-0,019	0,049	-0,019	-0,385	0,701	-0,116	0,078	0,948	1,055
MarP_9	-0,024	0,049	-0,025	-0,493	0,623	-0,121	0,073	0,945	1,058
MarP_10	0,030	0,049	0,031	0,608	0,545	-0,067	0,126	0,946	1,057

Normal P-P Plot of Regression Standardized Residual



Scatterplot



## Appendix D: Bull market regression model

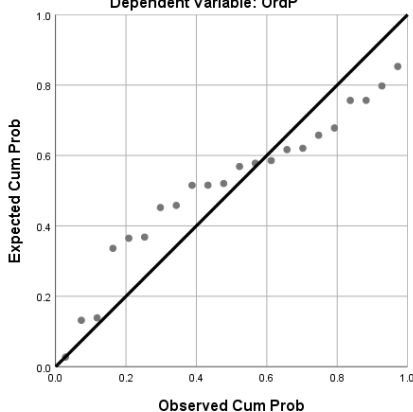
### Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.937a	0,878	0,745	0,02741	0,878	6,566	11	10	0,003

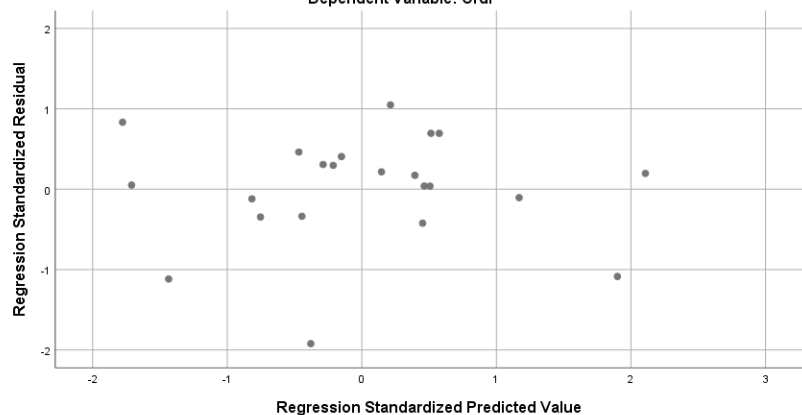
### Coefficients

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	99,0% Confidence Interval for B		Collinearity Statistics	
	B	Std. Error	Beta			Lower Bound	Upper Bound	Tolerance	VIF
1 (Constant)	-0,008	0,024		-0,316	0,759	-0,062	0,046		
MarP_0	0,966	0,158	0,904	6,100	0,000	0,613	1,319	0,554	1,805
MarP_1	-0,004	0,153	-0,004	-0,028	0,978	-0,345	0,336	0,595	1,681
MarP_2	-0,071	0,157	-0,067	-0,452	0,661	-0,422	0,280	0,549	1,822
MarP_3	0,020	0,163	0,019	0,124	0,904	-0,342	0,382	0,514	1,944
MarP_4	-0,009	0,158	-0,008	-0,055	0,957	-0,361	0,343	0,559	1,789
MarP_5	0,031	0,155	0,028	0,199	0,846	-0,314	0,376	0,597	1,674
MarP_6	0,030	0,169	0,028	0,180	0,861	-0,345	0,406	0,507	1,972
MarP_7	0,163	0,198	0,136	0,825	0,429	-0,277	0,603	0,450	2,222
MarP_8	-0,150	0,201	-0,121	-0,749	0,471	-0,598	0,297	0,463	2,160
MarP_9	0,072	0,200	0,054	0,361	0,726	-0,373	0,517	0,550	1,818
MarP_10	0,149	0,193	0,112	0,774	0,457	-0,280	0,579	0,583	1,716

Normal P-P Plot of Regression Standardized Residual  
Dependent Variable: OrdP



Scatterplot  
Dependent Variable: OrdP



## Appendix E: Bear market regression model

### Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.971a	0,943	0,912	0,01783	0,943	30,165	11	20	0,000

### Coefficients

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	99,0% Confidence Interval for B		Collinearity Statistics	
	B	Std. Error	Beta			Lower Bound	Upper Bound	Tolerance	VIF
1 (Constant)	0,001	0,005		0,141	0,889	-0,009	0,010		
MarP_0	0,924	0,057	0,924	16,235	0,000	0,805	1,042	0,877	1,140
MarP_1	0,102	0,056	0,103	1,818	0,084	-0,015	0,219	0,889	1,125
MarP_2	0,002	0,060	0,002	0,041	0,968	-0,123	0,128	0,893	1,120
MarP_3	0,030	0,058	0,029	0,510	0,616	-0,092	0,151	0,880	1,137
MarP_4	-0,067	0,059	-0,064	-1,130	0,272	-0,191	0,057	0,874	1,145
MarP_5	0,037	0,065	0,034	0,569	0,576	-0,099	0,173	0,785	1,274
MarP_6	0,071	0,066	0,065	1,079	0,293	-0,067	0,209	0,779	1,285
MarP_7	-0,038	0,062	-0,035	-0,606	0,551	-0,168	0,092	0,849	1,178
MarP_8	-0,041	0,061	-0,038	-0,671	0,510	-0,169	0,087	0,897	1,115
MarP_9	0,105	0,062	0,098	1,677	0,109	-0,026	0,235	0,838	1,193
MarP_10	-0,058	0,063	-0,054	-0,924	0,366	-0,188	0,073	0,839	1,192

