Do You Feel Like Buying Bitcoins?

The impact of emotions on financial markets

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Date: 8th of November, 2016

Abstract

Previous research examined the relationship between individuals' emotions and the impact these emotions have on financial markets. This paper made use of a lexicon-approach to analyse the relationship between Reddit comments and the bitcoin. Using an emotion lexicon and a database of 340,000 Reddit comments, models were built with the aim of establishing a link between emotions of individuals on Reddit's Bitcoin forum and the Bitcoin cryptocurrency. To support this endeavour, literature surrounding the concept of data mining, as well as financial literature related to human behaviour was analysed. Two models were created for the trading value of the Bitcoin and its transaction volume for the years 2012 through 2015. While the results reveal a mixed success of finding a relationship between the two concepts, they also indicate that further research within the domain of emotions in financial markets should be considered.

Keywords: Bitcoin, Cryptocurrency, Data Mining, Emotion, Emotion Analysis, Financial Markets, Reddit, Sentiment Analysis

Acknowledgements

I would like to dedicate this thesis to my friends and family who have always been therefore me to support me during my time of writing this paper, and before. First and foremost, I would like to thank my supervisor, Viatlie Spinu, without whom I would have never been able to write this thesis. His dedication and encouragement towards going further and digging deeper in my writing process were invaluable.

A big thank you goes to our behavioural economics thesis feedback session group including Linda Smolka, Monice Cornelissen, Rashiq Muhaimen, and others who I may have forgotten to mention. You have helped me in narrowing my topic and allowed me to understand that my work can never be good enough. Additionally, I would like to thank Pasi Rantanen, who managed to cheer me up and give insightful comments to this paper. Further, Prithvi Shashikant deserves a special acknowledgement as he was the only one of my friends who managed to grasp what my topic was and was therefore able to help me in figuring out technical issues which I was facing. Also, he had the brilliant idea to sign me up for a 36 hour/week commitment contract which worked well for the most time. Also, a warm thank you to Sten te Vogt and Poorvi Iyer, who volunteered to read my thesis in its final stage and offered great feedback and help whenever needed. Further, I would like to thank Victor Staak who was there in the final stretches of my thesis to aid me with the last bits of my data. Lastly, I would like to give the biggest shout-out to my brother, Manuel Kandzia, without whom the data mining would not have been possible. Without his help, the creation of the dataset would have dragged out this thesis by months. He was there to aid me with my code, and took it upon himself to help me with the implementation of whatever ideas I had during my thesis.

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Tables and Figures

Section 1 – Introduction

Historically, both policy makers and corporations were required to play the guessing game when it came to understanding people's preferences, tastes, attitudes, and feelings. Trying to understand the behaviour of humans to increase their respective goals, in the form of providing better service to its citizens by the state, or increasing the predictability of human purchasing behaviour are important topics in society today. However, recent advances in data analysis have been fruitful. Yet, failure in the implementation of policy, the introduction of products into markets, and the creation of financial bubbles are still problems faced today. While these seem to be three unrelated events, they often boil down to a misunderstanding of market behaviour.

Through the expansion of the internet for everyone, the largest trading place for cat pictures, and a world-encompassing discussion platform was born, and with it an unprecedented amount of data. The rise of the internet with its ever-increasing scope, has brought forth a tremendous number of new tools for both users and researchers alike. Using underlying subconscious search behaviour, companies like Google have managed to improve the accuracy of advertisements to help corporations at targeting individuals better. Recently, internet giant Amazon.com has introduced a predictive algorithm that will ship products to warehouses near individuals before they even make the purchase, by being able to predict individual's purchasing behaviour (Lomas, 2014). While large advancements have been made in recent years to utilise the behaviour of individuals through smart marketing based on search preferences, understanding the underlying drivers of human beliefs and sentiments remains a near impossible task.

Anomalies in financial markets can arise for a variety of reasons, intentional or unintentional. However, a still young field of sentiment analysis (or SA) can bring about large-scale change in this domain. Utilising the behaviour of single individuals and understanding the implications for larger groups can potentially help us eliminate, or at least mitigate, the negative side-effect of our financial systems. The potential of SA has not gone unnoticed by researchers and corporations, and due to its vast potential, they have begun to shift competencies towards this new field in recent years (Pang & Lee, 2008). The careful exploration of positive (favourable) and negative (unfavourable) sentiment can help to identify the opinions of individuals towards specific subjects (Nasukawa & Ji, 2003). By tapping into large sources of opinionated data, potential trends of sentiment can be extrapolated. The data, most often coming from social media, can be used for a multitude of purposes. One of the most famous examples of using SA is the prediction of elections. Researchers could predict the election results in Germany using messages users wrote on the microblogging platform

Twitter[1] (Tumasjan et al., 2010). A similar study has already been conducted to estimate the outcome of the 2008 presidential campaign using RSS feeds[2] (Wanner et al., 2009).

Recent findings on smaller scales already show remarkable effects. With new models in understanding human feelings, emotions, and sentiment, researchers have already been able to predict trading patterns in small-scale digital financial systems, called cryptocurrency markets (Shah & Zhang, 2014; Madan et al., 2015; Colliani, 2015). These markets are a lot less complex than traditional financial markets as (1) there are fewer active individuals in this market, and (2) they do not fall under the jurisdiction of any central bank or any comparable financial institutions.

Emotions have been clearly linked to having an impact in human decision making (Bechara et al., 2000; Schwarz, 2000). Research further suggests that investors make irrational decisions in financial markets (De Long, et al., 1990; Lee, et al., 1991; Bakker, 2003). The Bitcoin as a cryptocurrency is particularly interesting to study due to the lack of federal oversight mechanisms. This allows researchers to tap into a market that is very close to a libertarian market economy. To explore the predictive power of emotions a corpus of Reddit comments will be used, one of the largest websites for user generated content in the world, and the Bitcoin, the worldwide leading cryptocurrency. Therefore, I want to research the impact that emotions have on financial markets, by using the Bitcoin as a means of analysis. I will research the following question:

How do emotions impact financial markets such as the Bitcoin market?

To answer this question, we must understand several key aspects of both the Reddit and the Bitcoin. Without such understanding, the scientific and social relevance of this paper can become questionable. A detailed account of both the Bitcoin as a cryptocurrency and the Reddit as a social exchange platform will be given in sections 1.1 and 1.2, to broaden the understanding of these two terms. Afterwards, a literature will analyse existing research in SA and relate it to the Bitcoin and Reddit. An emotional framework will then be created which gives detailed accounts of eight emotions used in particular for this research in section 3. From this, hypotheses will be formulated in Section 4, which are aimed at helping answer the research question. Sections 5 and 6 will discuss the data and methodology which will be used for the analysis of the Bitcoin. The results of this paper will be discussed in section 6, and the final discussion and conclusion will follow in Sections 7 and 8.

[1] https://www.twitter.com
[2] RSS – short for Rich Site Summary – is a web standard extension used to publish short information regarding blog entries, news headlines, audio, or videos and generally consists of a summarised text similar to a live-ticker seen on many news networks.

1.1 – Bitcoin

The Bitcoin is a so called "cryptocurrency", a digital currency created in 2008 (Bitcoin Project, 2016). In its essence, a cryptocurrency is a unit of account which encompasses all five characteristics of money, namely durability, portability, fungibility, scarcity, divisibility, and recognisability. Bitcoins, unlike physical currencies given out by central banks, are created by users called "miners". To create, or mine, a Bitcoin, the miners use computers to solve complex mathematical problems (Bitcoinmining, 2016). However, the overall possible number of Bitcoins to exist is finite, and the farming of Bitcoins becomes ever more difficult with more Bitcoins in existence[3]. This system aids in making sure that the Bitcoin can indeed be assigned a value. As the maximum attainable number of Bitcoins is slowly reaching its physical limit, and the value of the Bitcoin has steadily increased, users can purchase goods with ever smaller denominators[4] (also called a Satisho, after the inventor of the Bitcoin). Users can store their Bitcoins in so-called wallets, highly encrypted Bitcoin storage programmes, which can then be used by the user to make transactions much like PayPal or other online banking systems.

While starting as a cryptocurrency, limited in its reach and ability to make transactions outside of a very small and confined community, the Bitcoin has come a long way. In November 2010, the market capitalisation of the Bitcoin reached more than US$100,000 for the first time. By April 2011 the market capitalisation reached US$1,000,000, by March 2013 one-billion US Dollars, and by June 2016, it has reached ten-billion US Dollars (Blockchain, 2016). The increased market capitalisation has several reasons, namely the forerunner position of the Bitcoin as one of the first cryptocurrencies, the early integration by many online shops, and lastly the media attention it gained during several instances like the bankruptcy of the biggest Bitcoin trading platform, Mt. Gox, large-scale fraud cases related to the Bitcoin, and the confusion related to labelling the Bitcoin as a currency or a commodity (Cuthbertson, 2015). Whereas the EU ruled the Bitcoin to be a currency (Schencher, 2015), the United States Commodity Futures Trading Commission (CFTC) classed it as a commodity (Kawa, 2015).

Since its creation, the Bitcoin has experienced several shocks and is considered relatively volatile compared to physical currencies. And while this volatility can be considered a potential weakness in protecting the investors from enormous shocks (Thobhani, 2016), it further reasserts the Bitcoin's freely floating exchange rate (Kaplanov, 2012).

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[3] The number of bitcoins is limited to 21,000,000 and it is estimated that by 2140 all Bitcoins will eventually be mined (Bitcoin Project, 2016).
[4] the smallest denominator of the Bitcoin is 0.00000001 BTC, called a Satisho, after the founder of the Bitcoin.

1.2 – Reddit

Unarguably one of the fastest ways for individuals to share their opinions and discuss these with friends and strangers alike is the internet. One of the biggest communities regarding the Bitcoin is the Reddit, a social networking site on which users can exchange information and engage in discussions regarding the Bitcoin. Due to the size of the community relative to the number of total transactions of goods and services through the Bitcoin it stands as a viable sample for the entire population of Bitcoin users (Blockchain, 2016).

While most research on sentiment analysis currently utilises the microblogging service *Twitter*, a recent post on the internet made available the vast amount of content of the social news networking site *Reddit*[5]. While the data has not been available for long, the initial interest in the dataset was large. On Reddit, users can link articles or post opinions about nearly everything, and other users can comment on the content, thus often leading to lengthy discussions among users. The vast potential of such a dataset already caught the eyes of researchers and corporations alike. Elon Musk's[6] artificial intelligence company OpenAI is using Reddit to teach an artificial intelligence supercomputer.

To understand the significance of the Reddit, one first must understand what the site is and how it functions. The site initially opened its doors in June 2005 as a means for people to share content with other users. What made the Reddit stand out from other content-sharing websites around the time was its unique way of organising content. Different sections of the Reddit are called subreddits. These subreddits are individual forums for people who share similar interests to engage with one another, and have their own rules and moderators making sure that only content specific to the subreddit is posted there. Some of the largest subreddits range from "funny", where individuals can post pictures, videos, gifs, or jokes which they enjoy and want to share with the world, to "AskHistorians", where actual historians (history-savy users) can engage in discussions, and help less-knowledgeable individuals with questions they have about specific topics (Reddit, 2016). Users of the site can subscribe to the subreddits they are interested in, thus creating a personalised Reddit for each user.

While the Reddit community as such may not be representative of the general population, the Bitcoin subreddit may however be more representative as a community to analyse since those who actively discuss the Bitcoin may also be likely to use the Bitcoin. On any given day, between 300,000 and 600,000 unique Bitcoin addresses may be used (Blockchain, 2016), and almost 200,000 individuals are subscribed to the Bitcoin subreddit (Reddit, 2016), the overlap between these two groups is likely to be very large.

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[5] https://www.reddit.com/r/bigquery/comments/3cej2b/17_billion_reddit_comments_loaded_on_bigquery/
[6] Founder of PayPal, SpaceX, and Tesla Motors

Section 2 – Literature Review

So far, the research on sentiment and emotion is still scarce. While reasonable progress has been made, the data is still scattered and unearthed. In the following section an overview of the specific terminology as well as implementations of SA that researchers have already made will be given.

Emotions are considered the most basic human feelings (Plutchik, 1980). First scientifically documented by Darwin, it is now common understanding that evolution does not only derive from the mutation of physical features, but more importantly, from an evolution in the brain. By developing emotions, primal instincts are slowly replaced. Psychology has since developed several theories regarding the importance of emotions in a social context (Lutz & White, 1986; Karstedt, 2002; Shilling, 2008). Recently, the study of emotions has gained momentum again. Due to the possibility of using state-of-the-art technology and the emotions mined by thousands of people online, a near-endless amount of applications seem to be possible for the task of understanding the impact of behaviour on society. SA is one of these hotbed topics. Using sentiment, or emotions, researchers are now trying to understand why people do what they do.

One of the earliest pieces of groundwork for this research comes from Ekman (1992). He established a fundament of basic emotions which have their own set of characteristics. These emotions were joy, sadness, anger, fear, disgust, and surprise. This emotional framework has been used by other researchers more recently. Strapparava and Mihalcea (2007) for example, used the six emotions proposed by Ekman to find emotion and sentiment in newspaper headlines. The objective of their doing was to understand how emotions may have different effects on the readers of newspaper headlines. Plutchik (1980), in his book, argued for eight basic emotions: the six which were explained previously plus trust and anticipation. He describes the importance of emotions as an evolutionary requirement. His list of emotions is based on his research stemming from evolutionary history in which he further created a wheel of emotions (see Appendix 1), which serves as a means of understanding interactions between emotions. Sentiment, on the other hand, is a binary opinion or feeling towards something or someone. This binary feeling is generally separated into positive and negative only (Pang & Lee, 2002). Sometimes a third category is added to the binary setting, namely "neutral", for objective statements without any sentiment attached to them. Compared to the emotional framework consisting of several different emotions, which can occur simultaneously, any statement can be interpreted as only one of the two (or three) sentiments.

An early account of SA as we know it today stems from a paper by Dave, Lawrence, and Pennock (2003) in which the authors coin the term "opinion mining". They proposed to construct an opinion mining tool to "process a set of search results for a given item, generating a list of product attributes (quality, features, etc.) and aggregating opinions about each of them (poor, mixed, good)" (Dave, Lawrence & Pennock, 2003). It is important to note that opinion mining and SA are synonyms with personal preference dictating the choice of terminology (Liu, 2012). The trio's approach involved grouping of sentences into specific attributes to draw conclusions regarding an individual's opinion towards a product.

While SA has received a wider gain in academic popularity in recent years, the focus of SA still seems to be development of reliable models (Pang & Lee, 2004; Wilson, Wiebe, Hoffman & Hoffmann, 2005). The most widely used application of SA is the creation of an SA tool. In SA, large corpuses of data are collected, analysed, and prepared so researchers can draw conclusions about the opinions of large crowds towards a certain – mostly cultural – phenomenon (Pak & Paroubek, 2010). However, through ever more potent computing power, machine learning methods in natural language processing have become a task that can be carried out from offices without the aid of state-of-the-art supercomputers (Pang & Lee, 2008). And while a few years ago, concepts like data mining and big data were only known by few, and carried out by fewer, the modern computers can cope with most processes involving (simple) analyses of large datasets.

Related work in the field of sentiment/ emotion analysis is not vast, however the documented resources are very detailed. Mohammad et al. (2014) found that tweets nearly always reflect the sentiment of the person who wrote them, and not that of the target at whom they were aimed. This is an important take-away as it helps us to understand how we can assess the context in which texts should be seen. Pang and Lee (2008) used SA to analyse product reviews, and subsequently were able to assess which reviews were most likely to be considered important by individuals who are currently researching a new purchase. The predictive power of twitter-based SA has been proven by several studies to date (Go et al., 2009; Colianni et al., 2015). Pixley (2004) researched the consequences of negative emotions like fear and greed in the financial world. She points out that emotions mainly drive speculations. Pixley (2002) finds a large impact of psychological concepts in modern economics. As firms are run by people, they commit the same mistakes as individuals. Herd behaviour and the animal spirit are found to be large drivers of modern financial corporations.

The advancements towards using SA have not only attracted academic researchers, but in recent years also corporations. Especially *Twitter*[7], the biggest microblogging service in the

[7] https://www.twitter.com

world, is now being used as a tool by marketers around the world to extract human sentiment (Kouloumpis, Wilson & Moore, 2011). Twitter is also the preferred data source for most academic researchers (Pak & Paroubek, 2010; Agarwal et al., 2011; Wang et al., 2011, Wang et al., 2012). The use of *Twitter* became established due to the service's ability to connect millions of people in real time. Twitter however is restricted in some sense. Specifically, users cannot post anything longer than 140 characters. This restriction can make it difficult for some to state their mind thoroughly. Furthermore, the nature of Twitter itself makes discussions among users rather complicated. While it is possible for two or more users to engage in conversation, the lack of clear structures creates a linear conversation, as opposed to a multifaceted discussion in several layers, and involving a multitude of users, as seen on the Reddit.

The possibility of mining, understanding, and lastly interpreting sentiment[8] of a full Reddit corpus as done in this paper is only made possible through the groundwork previously done by other researchers. Saif Mohammad (Mohammad, 2016), has taken it upon himself to create lexica which interpret words based on the strength of the emotions in which they are mentioned. Most research in the field of SA revolves mainly around natural language processing (NLP) and machine learning approaches, fields of computer science mainly concerned with the computer-human interaction such as that in online communities to let technology automatically group texts or pictures into specific categories (Pang et al., 2002; Wiebe, Wilson & Cardie, 2005).

[8] While mainly using the term SA or sentiment analysis in this paper, this is only done to facilitate the overall spectrum of the field and also to simplify the terminology. The main research in this paper will regard emotions rather than sentiment.

Section 3 – Emotional Framework

Prior research on the role of positive and negative sentiment has shown that sentiment strongly affects decision-making (Damasio, 1994; Valention et al., 2011). Emotions which stem from certain types of sentiment are therefore suggested to have a profound impact on financial decision making alike. Negative emotions are often linked to a situation in which individuals try to avoid harm (Gray, 1990). This implies that individuals experiencing negative emotions will act less on positive market trends. On the other hand, positive emotion is said to cause the direct opposite behaviour; a positive emotion stimulates optimistic decision making (Cacioppo et al., 1999).

It is important to note that no emotion can be inherently categorised as strictly positive or negative. To understand whether an emotion is truly positive or negative, one must understand the context in which the emotion is present, and the type of interaction that precedes the emotion at hand (Plutchik, 1980). Events that may cause joy for some may lead to anger in others. Following, the eight emotions researched by Plutchik will be analysed and explained in further detail.

To understand the implications of emotions on financial decisions, we will first have to establish our understanding of these emotions. The following section will provide a more detailed account on the emotional framework of financial decision making. Subsequently, hypotheses will be created based on the predictions and findings of previous research on financial decisions under the influence of different emotions.

3.1 – Anger

Counterintuitively, anger is not perceived as a negative emotion by many researchers (Plutchik, 1980; Lerner et al., 2004). Anger is one of the most basic emotions acquired through evolution itself and causes feelings of empowerment and confidence. Lerner and Keltner (2001) conducted research based on the risk attitudes of individuals. They used the perception of risk to create a framework in which emotions were analysed in financial markets. The duo concluded that anger in individuals invokes a more optimistic risk assessment. Gambetti and Giusberti (2012) conducted a study on financial decision making with regards to risk in decision making. They found that individuals with a strong tendency to show anger also have a higher tendency of committing to riskier decisions, and therefore a more optimistic outlook. Han et al. (2007) found that, unlike fear, anger is defined by a positive assessment of a situation. The higher degree of optimism causes anger to catalyse into a brighter outlook.

Current research on the domain of anger suggests a very one-sided, however slightly counterintuitive behaviour of individuals. Anger is thought to make people and investors become optimistic, thus increasing their tendency to invest.

3.2 – Anticipation

Anticipation is a less direct emotion as it often enhances other emotions. Anticipation is "act of preparing for something" (Merriam-Webster, 2016). Anticipation implies at least a degree of uncertainty or risk. Kuhnen and Knutson (2005) explain that investors systematically deviate from making rational choices in the face of financial decisions. Their research suggests that being faced with a large degree of anticipation will cause investors to make mistakes. Anticipation also causes individuals to think more future-oriented. For investors, this implies that they will act based on their best judgement of future changes in the market (DeFond & Park, 1997).

It is difficult to understand the implications of anticipation in the context of an individual's decision making ability. To understand how anticipation promotes error making, one has to consider the notion that individuals are often subject to time-inconsistent decision making. Anticipation is the manifestation of this behaviour, as it regards the utility one receives from possible future events. The emotion is dependent on a state of risk of uncertainty in the present, which in turn creates situations in which sub-optimal, or even outright irrational decisions can lead to investment mistakes. Therefore, the uncertainty experienced through anticipation may lead to investors establishing simple links between their emotions and investment decisions.

3.3 – Disgust

Literature finds that disgust is strongly related to anger as an emotion. However, as opposed to anger, disgust does not entail the desire to act upon the emotion (Plutchik, 1980). Whereas anger causes the desire to act, disgust can often lead to content. Lerner et al. (2004) examined the effect of disgust and sadness on economic decisions. While these two emotions are often associated with another, the actions taken through these emotions do tend to differ vastly. Disgust, the trio found, causes an "implicit action tendency to expel current objects" (Lerner et al., 2004) and causes individuals to not pursue any new operations.

The research on disgust as an emotion in decision making suggests that individuals will become more likely to cease operations, and therefore become less likely to start a new endeavour, at least in the short term. This can lead to a situation in which individuals want to sell their financial products, and makes them less likely to procure new operations in the short term. As opposed to sadness which tends to create a more reflective state of mind, disgust appears to cause an immediate emotional response to certain actions.

3.4 – Fear

Fear is an emotion that is usually triggered by a feeling of threat or danger, but also great uncertainty. Lerner and Keltner (2001) concluded that, as opposed to anger which causes optimistic risk assessments, fear has the opposite effect and drives investors towards more negative assessments of risk (Haidt et al., 1994). This negative risk assessment causes individuals to make pessimistic choices about future events. Slovic et al. (1987) pointed out that emotions are the main driver of people's risk perception. And fear especially seems to be very influenced strongly by one's appraisal of risk and uncertainty (Lo et al., 2005). Specifically, fear is said to be defined by a low appraisal pattern and situational control (Han et al., 2007)

Like disgust, fear seems to cause individuals to be more likely to make sub-optimal decisions. As previous research suggests, the impact on an individual when experiencing fear is the opposite of that when experiencing anger. Fear is a primal emotion, often associated with negative future consequences. And while anger may lead to an uptake in thought-provoking critical thinking to reduce the impact of a negative consequence, it seems that fear causes the opposite. This negative risk-assessment could translate into a situation where individuals cease their current financial operations and try to sell the products they already possess.

3.5 – Joy

Joy is a positive emotion often associated with confidence and contentment (Plutchik, 1980). In this way, it shares certain characteristics with anger. Like anger, joy is positively associated to an increased amount of optimism, certainty, and control. Research suggests that actions taken by people experiencing joy are like those who experience anger as an emotion (Ellsworth, 1985; Han et al., 2007). Huang and Goo (2008) researched the effects of environmental and situational impacts on investors. They found that when the investment atmosphere is good, investors tend to be overconfident. Their research also suggests that environmental effects tend to have little impact on the investor's overconfidence. Joy or happiness also stands in contrast to anticipation. While anticipatory joy does exist, the joy of outperforming other investors, who miss-anticipated an event, seems to be much more satisfying to investors (Merkle et al., 2014).

Research suggests that joy leads to confidence and optimism. Evidence exists that investors are especially impacted by the market they operate in themselves, and less so by outside factors (Huang & Goo, 2008). This finding is both interesting for joy, but also the remaining emotions. If the overwhelming impact on a person's investment decision arises from the mood on the market, outside noise may be less of an issue than previously expected. Choices undertaken by experiencing joy can also be observed for a very different emotion, namely anger. Whether joy and anger do share large similarities in terms of actions taken by individuals experiencing them will be analysed.

3.6 – Sadness

Often considered the most common negative emotion, sadness includes feelings of discouragement and general dissatisfaction. Han et al., (2007) point out that sadness often co-occurs with appraisals of situational control. This implies that sadness causes individuals to put blame of failure on situational factors as opposed to angry individuals who seek blame in individuals within the environment. Sadness therefore comes from a reflection from within and the thought that the situation or environment is at fault of failure, as opposed to individual failures which cause anger (Keltner et al., 1993). However, sadness is also a driver of empathic responses and a general desire to change something (Plutchik, 1980; Raghunathan & Pham, 1999). Most often, sadness requires the action of the individual. Sadness can be understood as a motivation to finding something rewarding (Raghunathan & Pham, 1999). Shu et al. (2016) examined the impact of sadness through the bereavement of fund managers. Their study suggests that sadness among fund manager's increases risk adversity, impatience, and risk-sensitivity.

Sadness, as one of the strongest and most primal emotions, is important to understand. Researchers have spent vast amounts of time on understanding the impact of sadness on our actions. Findings suggest that individuals while becoming more aware of their actions, and how they need to react to counter their state of mine, often become more risk averse and impatient. This could imply that sadness is a state that individuals want to leave as soon as possible, by making small, and riskless choices to give them some sort of fulfilment.

3.7 – Surprise

Surprise is an extremely strong emotion caused by an unexpected event. This emotion is strong enough to override consciousness, however depending on the type of surprise, it can either lead to a positive or negative mindset (Plutchik, 1980). Surprise most often occurs without any anticipation prior to the event, or if the opposite of the anticipated outcome occurred. Specifically, surprise occurs when an event occurs that was prior not anticipated at all, or deemed extremely uncertain (Preuschoff, 2011). Much research has so far been attributed to the impact of risk in decision making. However, much less is known about decision making under uncertainty, and the subsequent imposition of a surprise moment (Hsu, et al., 2005).

Surprise is, similarly to anticipation, an emotion which seems to influence other emotions. Research identified that positive and negative surprise have different consequences. However, unlike anticipation which is an emotion regarding events that are bound to occur in the future, surprise is an emotion occurring due to a change in the present.

3.8 – Trust

Trust is a strong underlying emotion evoked through familiarity (Plutchik, 1980). Not only is at an important feature human interaction, but also a requirement for nearly every part of human culture. Especially modern financial markets are dependent on trust, as without it markets would experience high volatility, and potentially collapse due to a high amount of risk associated with anything that is not trustworthy (Mayer, 2008). Recent research has brought forth that especially for internet based financial decisions, trust is the most important factor for a consumer (Kim et al., 2008). In his book, Fukuyama (1995) highlights that for any economic endeavour to flourish, individuals need to have trust in it. This trust is built through a variety of ways. Specifically, the author highlights the importance of commonly shared norms within countries as a means of creating trustworthiness. Only by gaining trust, can growth occur.

Trust is one of the key elements of our society. The ability to trust people, given that laws and regulations can help assert positions creates security and cooperation among people. Especially social norms can help to create such a trust. In academic literature, these norms are explained through similarities among citizens within specific groups (Plutchik, 1980). The Bitcoin community fulfils such a perquisite as well. Due to the common interest in a (relatively niche type of financial product) and a somewhat familiar environment with likeminded people engaging in discussion, the Bitcoin subreddit may act as a trustworthy community.

Section 4 – Hypotheses

To analyse the aforementioned emotions within the context of this research paper, several hypotheses will now be established and explained.

Firstly, literature suggests that anger, disgust, fear, joy, sadness, and trust can all have an impact on the trading price of a financial commodity. Anger was found to create a feeling of confidence. Disgust and fear lead to a ceasing of operations and a lack of trust in the financial product. Joy, while being caused by very different reasons than anger, was found to share similar properties with it in terms of optimism. Sadness was found to relate to increased risk-aversion and a likely discontinuation of operations. Trust creates a sense of safety and righteousness in the system, thus being able to strengthen the willingness to invest. Therefore, the following hypotheses were created:

$$\boldsymbol{H1_a: Anger\ , joy, and\ trust\ lead\ to\ an\ increase\ in\ the\ value\ of\ the\ bitcoin}$$
$$\boldsymbol{H1_b: Disgust, fear\ and\ sadness\ lead\ to\ a\ decrease\ in\ the\ value\ of\ the\ bitcoin}$$

Anticipation, as an emotion is future oriented. In other words, it tries use information available today to make assessments about the future. The difference between anticipation and the aforementioned emotions is that it does not seem to occur independently of other information and uses rationale to draw conclusions. For this reason, anticipation will be assessed as a variable that is also dependent on current information. Therefore, the hypothesis created for anticipation is as follows:

$$\boldsymbol{H2: The\ interaction\ between\ anticipation\ and\ the\ value\ of\ the\ Bitcoin}$$
$$\boldsymbol{is\ related\ to\ the\ future\ value\ of\ the\ Bitcoin}$$

The literature seems to imply that disgust, fear, sadness, and trust have a strong secondary implication related to financial markets, namely that they are not only affected with a change in the value of a financial product, but also with its trading volume. Additionally, anger and joy, being demand enhancing emotions, seem to give an indication of direction in investor behaviour. An increase or decrease in one of these emotions could cause the abortion or active engagement in a market transaction, and thus increasing or decreasing the volume of trades. Therefore, I hypothesise that:

$$\boldsymbol{H3_a: Anger, joy, and\ trust\ lead\ to\ an\ increase\ in\ the\ transaction\ volume}$$
$$\boldsymbol{of\ the\ bitcoin}$$
$$\boldsymbol{H3_b: Disgust, fear, and\ sadness\ lead\ to\ a\ decrease\ in\ the\ transaction}$$
$$\boldsymbol{volume\ of\ the\ bitcoin}$$

Lastly, surprise takes a special role in the emotions. While having a unique interpretation to it like anticipation, surprise is very different from the remaining emotions. While anger or disgust are very specific and definite emotions leading to sentiment, surprise acts rather like a catalyst for other emotions. An unexpected event, such as a shock on financial markets is an event that triggers surprise, however, only if the degree of surprise is large enough. Therefore, I hypothesise the following as my last hypothesis:

$\boldsymbol{H4_a}$: $\boldsymbol{Large\ degrees}$[9] $\boldsymbol{of\ surprise\ have\ an\ impact\ on\ the\ price\ of\ the\ bitcoin}$

$\boldsymbol{H4_b}$: $\boldsymbol{Large\ degrees\ of\ surprise\ have\ an\ impact\ on\ the\ transaction\ volume\ of\ the\ bitcoin}$

Subsequently, the data and methodology of this research will be explained in full. By analysing the abovementioned hypotheses, we can gain a deeper insight into the emotional framework that surrounds trading activity. Furthermore, the hypotheses will aid in answering the research question of whether emotions influence the price of the Bitcoin.

[9] A large degree will be defined as a day in which surprise is the most prominent emotion using a dummy variable.

Section 5 – Data

5.1 – Reddit Corpus

The Reddit corpus was made available through the Reddit API. The dataset itself was made available through Google Big Query, an online tool through which very large datasets can be stored and accessed by everyone. By running a Query on the entire Reddit dataset of over 1 terabyte in size, only the required parts of the dataset needed for this paper could be extracted. A query was run on the comments based on the following subreddits: Bitcoin, BitcoinMarkets, BTC, BitcoinStocks, and CryptoMarkets. The largest of these subreddits, namely Bitcoin, has a reach almost 200,000 users. Overall more than 360,000 posts, and 4.8 million comments were collected this way. In its pure form the datasets were still very large and required additional attention. Below is a breakdown of the different subreddits.

Table 1 - List of Subreddit Metrics

Subreddit	**Subscribers***	**Subreddit Rank***	**Growth****	**Established on**
Bitcoin	180,463	237	7.3%	Sept 9, 2010
BitcoinMarkets	22,023	2,229	11.4%	Apr 1, 2013
BTC	17,847	2,683	11,1250%	May 20, 2011
BitcoinStocks	2,129	12,659	(-)7.7%	May 27, 2013
CryptoMarkets	5,713	6,591	4.4%	Nov 13, 2013

*Retrieved on June 19, 2016 from Redditmetrics.com
**Compared to June 19, 2015 data

In a next step, the data had to be cleaned. This process required a large amount of manual work. The subreddits in question are subject to several Subreddit specific anomalies, as well as Reddit specific anomalies which had to be removed. As a starting point, all posts by Redditbots had to be removed. These programs created by Reddit staff or subreddit moderators can comment on posts when they are triggered (through a specific word or phrase), or when they are explicitly summoned by a user through a specific word or phrase as a comment. A bot used often on a subreddit can therefore skew results by having a similar phrase used in many comments. A comprehensive list of these bots was available online, so any post from an author on this list was removed (Reddit, 2016).

To increase the precision of the data, not every comment was used for the analysis. Specifically, due to the way in which Reddit functions as a discussion tool for members, discussions can drift off-topic. A post about a specific topic may receive 100 comments. These comments must be differentiated into direct comments, and various degrees of indirect comments. A direct comment is one in which the author replies directly to the post made by the original author of the post. An indirect comment is one which replies to a comment. These indirect comments can be of various degrees. Reddit does not have any rule on how far out indirect comments can reach. Some subreddits haven even taken it upon themselves to use this system to create very long counting chains (Reddit.com/r/counting, 2016).

Figure 1 - Example of the comment section of Bitcoin subreddit

Figure 1 depicts a regular discussion on the /r/Bitcoin subreddit. At the very top, the title of the post can be seen – in this case a link to a news article. The commenters can choose to either reply directly to the post, or reply to a comment made by another user, thus being able to spark discussions related to a comment.

Comments of a certain degree of indirectness to the main topic, can often start a sub-discussion on their own. This means that people will no longer discuss what has been posted, but something someone commented. Often, these indirect comments can also be used to simply poke fun at something, make a joke, or a simple pun. This greatly reduces the accuracy of the dataset. These comments are not relevant to our analysis as they add no value to the discussion, and hence the emotions that are entailed within these comments are most likely irrelevant to our analysis. In the image depicted above, user "vqpas" spins the discussion to poking fun at Enron, a defunct company which was involved in large-scale accounting fraud, which is already too far removed from the actual post.

Similar research in the domain of sentiment using the same Reddit corpus has brought some light into understanding just how quickly comments can change the topic of their discussion. Jakić (2015) studied how media can affect sentiment. For this purpose, he used the Reddit corpus to analyse individual's sentiment in the comments of news articles posted on the website. Jakić used human annotators which manually read through hundreds of comments regarding specific topics on the Reddit. These annotators then had to state whether the comments were related to the post itself, or unrelated to this. By using several annotators, human error was minimised, as a score only counted based on a statistical measure called the Cohen's Kappa. This is a statistical measure for inter-rater agreement of qualitative items. The Kappa score is generally thought to be a robust measure of agreement between parties. The results of this test show that the direct comments to the post yield a Cohen score of 0.92, which relates to a large level of agreement between the annotators. Consequently, the first indirect comment only claimed a Cohen score of 0.49, implying only about half of the comments related to a direct comment of a subject are still related to the original subject. Further down the comment tree, the score becomes even lower.

In short, the final corpus of Reddit data consisted of the 340,278 cleaned comments in the timeframe of 2012 through 2015. Earlier data was omitted as the subreddits were too small which yielded in days without data. Later data was omitted due to it only being added to the Big Query database after work on the dataset had already begun. These comments stemmed from the five Bitcoin- and cryptocurrency-related subreddits described in Table 1. The data was cleaned in several different ways. First, all Redditbots and comments summoning those bots were removed. This was largely done manually after obtaining a list of all the bots. Afterwards, the dataset was further reduced as only the direct comment and the next two comment levels from the comment-tree depicted in Figure 1 were used. The reason behind this was the finding by Jakić that comments become less and less informative the further one ventures down the comment-tree.

5.2 – Emotion Lexicon

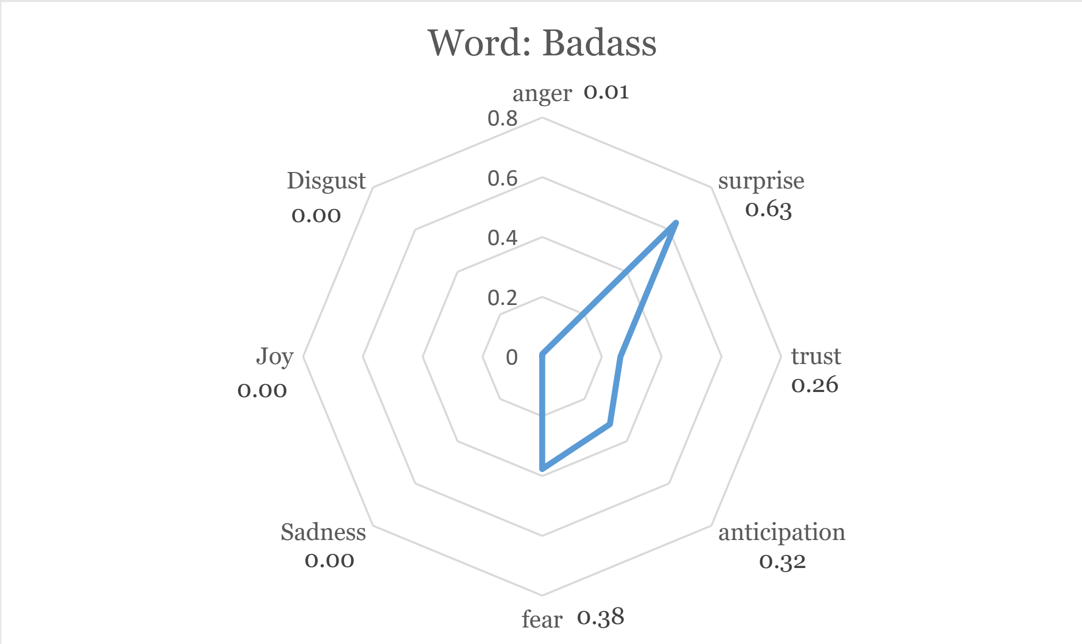
For this research, Saif Mohammad's *NRC Hashtag Emotion Lexicon* (Mohammad, 2016) was used. This lexicon is a corpus consisting of over 14,000 types of words based on Twitter posts (tweets). An important aspect of this lexicon, apart from being one of the most extensive ones to have been created to date, is its inclusion of words that can be described as internet jargon. Examples of this include emotions regarding smileys (or emoticons), intentionally misspelled words, and words or characters which symbolise emotions (e.g. "hahaha"). To build the lexicon, Mechanical turks, people who make a living of answering surveys or solving riddles online, were used to create this Lexicon. For this, thousands of tweets were collected from Twitter. These tweets were collected specifically as they contained hashtags using different emotions. Words and phrases preceded by the hash sign (hashtag), are often used in social media to identify a specific topic or message (Dictionary, 2016). Afterwards, a large number of Mechanical Turks manually gave every tweet a score between 0 and 100 in indicating how much they agree with the written text and the associated emotion of the hashtag. Through a machine learning approach, the individual words of the texts or tweets were then analysed and through an algorithm, every word was given an individual score for an initial list of 19 emotions. The higher the score, the stronger the emotion. Finally, Muhammad combined specific emotions to create the final eight. This was done because several emotional categories are highly correlated, and simply do not occur enough to stand robust on their own. Furthermore, it creates a narrower spectrum of emotions which are less correlated with one another. The following table provides the final eight emotions, and which other emotional categories they consisted of.

Table 2 - Breakdown of Emotions (Mohammad, 2016)

Emotion	**Influencing emotional categories**				
Anger	Anger				
Anticipation	Anticipation	Vigilance			
Disgust	Disgust	Dislike	Hate	Disappointment	Indifference
Fear	Fear				
Joy	Joy	Calmness			
Sadness	Sadness				
Surprise	Surprise	Uncertainty	Amazement		
Trust	Trust	Acceptance	Admiration		

To visualise the use of the emotions, a radar diagram was created to give a fast overview of how the emotions are at play for a given word. The radar diagram entails eight axes, each one depicting one emotion. A single word within the NRC-EmoLex can have between one and all eight emotions present, each to a different extent. The word "badass" for example shows surprise, trust, anticipation, and fear, while not influencing sadness, joy, disgust, and anger.

Figure 2 - Radar diagram depicting emotions related to the word "badass"



While researchers can identify a much larger amount of emotions which may strongly affect our behaviour and overall sentiment, these eight are the most individually robust emotions. Pearl and Steyvers (2010) focused their analysis on emotions such as politeness, formality, persuasion, and deception. Francisco and Gervás (2006) use pleasantness, activation, and dominance for an analysis of speech within fairy tales. However, a lack of reliable data surrounds these emotions. By extending the amount of researched emotions beyond our chosen eight we can encounter a lack of accuracy in the depiction of emotions within a text. Lastly, the use of too many emotions leads to strong degrees of correlation among the terms as mentioned earlier. Already we experience a word, such as the one depicted above, entailing several different emotions depending on their meaning within a text.

It is important to understand the possible implications of sarcasm on the data. The notion of sarcasm was also an important one to consider for this thesis. Filatova (2012) annotated Amazon product reviews for sarcasm and irony. Davidov et al., (2010) used Amazon product reviews as well to understand sarcasm. Lastly, Carvalho et al., (2009) annotated newspaper articles for ironic remarks. While the identification of the #sarcasm term may work well for twitter, the Reddit uses a different type of writing style, and it is therefore not possible to analyse posts this way. The most widely used method for symbolising sarcasm on the internet is the use of a "/s" at the end of a post. After scanning for the use of this, two important findings were made: first, the use of sarcasm seems to be low with less than 700 potential findings, and secondly, the use of "/s" was mainly done by users telling others that they forgot to use it. Written texts are even harder to analyse for sarcasm or irony than the spoken word.

For reasons of complexity and an apparent lack of true sarcasm within the dataset, the issue was not deemed as intervention-worthy.

Another advantage of the NRC-EmoLex is that it makes manual stemming of words unnecessary. Stemming is a method of reducing words back to their basic form, like removing the “s” in the end of a plural (Porter, 2016). This can be done to normalise the words in a document and reduce the amount of words needed for analysis. While generally a good approach to capture as many words as possible to analyse, the hashtag lexicon includes every word individually. This can increase the accuracy of an emotion, as perhaps a specific word may have a different connotation depending on the tense or form it is written in, but also how it is used within a sentence. The following table gives an example of a word, the emotions it encompasses, and several different versions of the word.

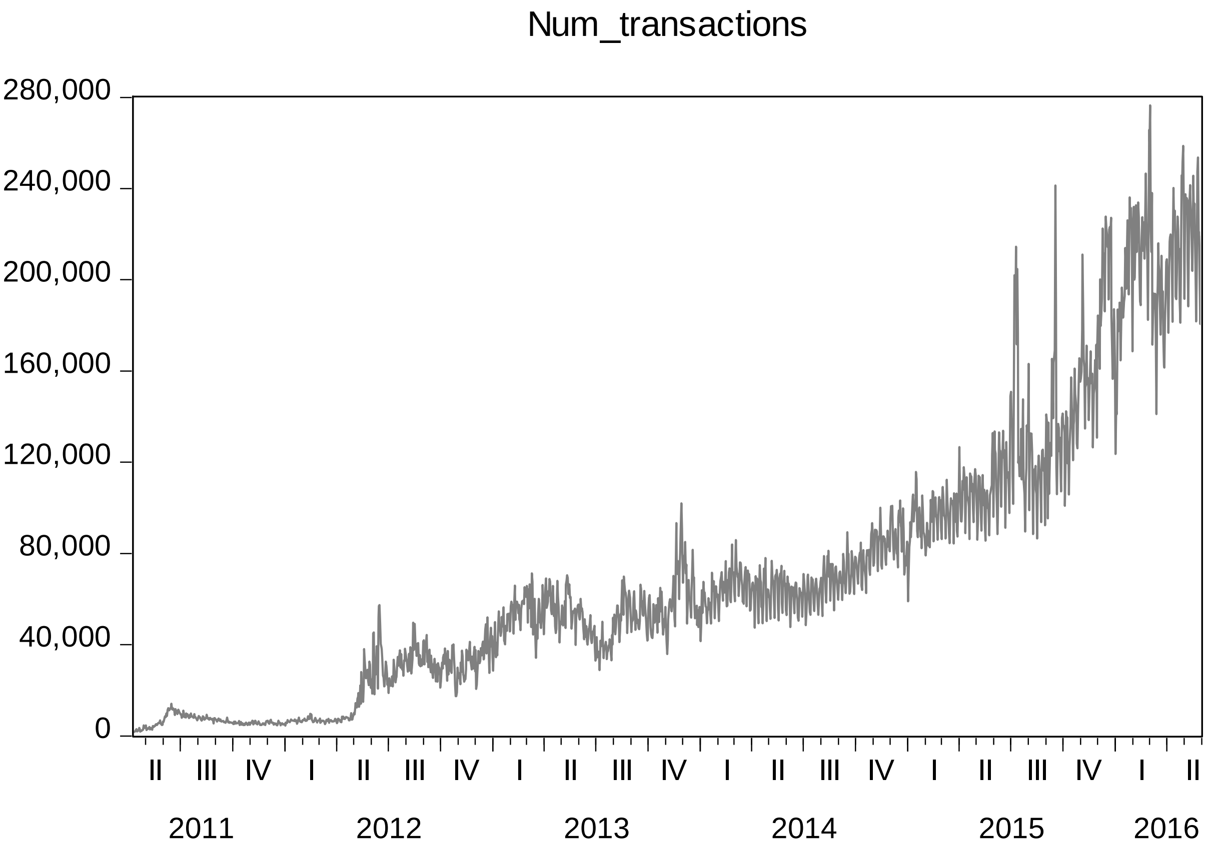
Table 3 - Example of stemming in the Emolex Corpus for the word "bake"

Sentiment	**Word**	**Score**
Fear	bake	0.333036949
Surprise	bake	0.079909673
Sadness	bake	0.390356351
Joy	bake	0.143902068
Anticipation	baked	0.412928804
Surprise	baked	0.066168045
Joy	baked	0.120590989
Disgust	baked	0.006434072
Surprise	baker	0.098957868
Anger	bakery	0.513624683
Anticipation	baking	0.360560818
Surprise	baking	0.26758058
Joy	baking	0.802192178

5.3 – The Bitcoin

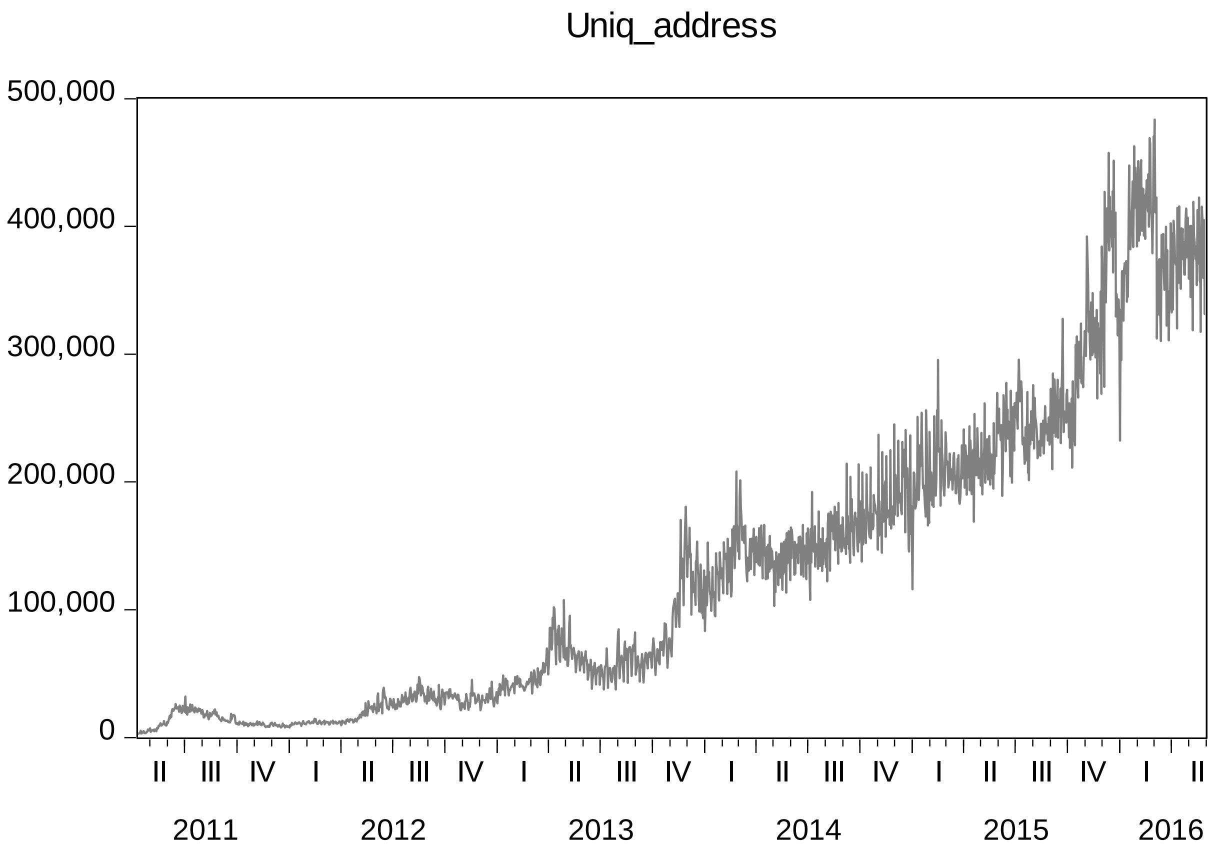
The Bitcoin's special status as a currency has for a while now interested data scientists (Alec et al., 2015; Colianni et al., 2015; Madan et al., 2015). Especially the ease of accessing data regarding the Bitcoin and the lack of restrictions in its trading are important to many investors. Furthermore, since its legitimisation by the EU, the Bitcoin has been treated like an actual currency thus causing more trust in the system. While economists have argued for and against the Bitcoin, its existence and increase in popularity for several years prove that it is a serious financial asset and should receive also academic attention (Krugman, 2013; Velde, 2013). Being the first and only successful cryptocurrency, the Bitcoin holds a special place in online financial activities. Due to its large awareness, the amount of daily transactions occurring with Bitcoins has also spiked in recent times. Figure 2 shows the daily number of transactions with Bitcoins since April 2011.

Figure 3 - Graph of the number of transactions using bitcoins between 2011 and 2016



Like the number of transactions, the number of individuals using the Bitcoin has increased even more rapidly in recent years, as can be seen in Figure 3. At its peak, the graph below shows nearly 500,000 different users making trades with Bitcoins on a single day. The number of users is determined through their unique user ID. While one individual can have several user IDs, it is unlikely that these users cause a significant difference in the overall Figure. Similarly, in some occasions, a group of people can own a Bitcoin wallet together, just like married couples sometimes have only one bank account.

Figure 4 - Graph of the number of unique addresses making transactions with the bitcoin between 2011 and 2016



Data regarding the Bitcoin will be collected from Blockchain.info, one of the largest Bitcoin wallet providers and fintech companies on the market (Kleinman, 2015). Blockchain.info collects data for currency statistics, block details, mining details, and network activity regarding the whole Bitcoin blockchain (Blockchain, 2016). For our main analysis, especially the market price of the Bitcoin (in US Dollars) will be of importance to us, which Blockchain.info calculates as the average price among the largest Bitcoin trading platforms. For further analysis, I will also include the number of transactions per day, the number of unique IDs taking part in a transaction per day, and market capitalisation.

Section 6 – Methodology

To understand the possible relationship between the financial markets and underlying emotions, econometric models will be created assessing the price changes of the Bitcoin with regards to the eight emotions introduced earlier. Specifically, I will analyse every hypothesis set up to be able to answer the research question. For this, at first the Reddit data must be acquired and analysed separately. Afterwards, the Bitcoin data will be added to the existing data to create models.

6.1 – Transformation of Emotions

To make use of the vast amount of content on the Reddit, Google's BigQuery was used. The platform already contained the previously uploaded data of all Reddit comments and posts. A simple script made it possible to store the data on a Cloud Storage platform and subsequently download it. Next, the data had to be analysed with the previously selected NRC Hashtag Emotion Lexicon. I broke up the comments by words to make it easier to treat them for the following steps. As the words had no quantitative implications, a script was written to check every word in our database of Reddit comments for a counterpart in the NRC Lexicon. If a match was found, the word then received a score on the eight-dimensional emotion list. If a word from the database was not found within the Lexicon, it was subsequently deleted as to reduce the amount of space the project required.

In a next step, the words were analysed for negators. If a negator (e.g. "not" or "n't") was present in front of a word, the score of the word was turned around. This means that a word like "badass", as depicted in Figure 1, would receive a negative score if the word "not" was placed in front of it. This means that if someone wrote "this isn't badass", the subsequent scores for surprise, trust, anticipation, and fear would become negative. Subsequently, every emotion the word invokes, surprise, trust, anticipation, and fear, would now receive a negative score.

The direct approach of matching words to a lexicon was used for two reasons. Firstly, the amount of effort required to create a more complicated model which engages in machine learning was not feasible for this project. Neither the time, nor the know-how for such an endeavour was available. Secondly, other research engaging in more complex methodologies often found only marginally better results of their analysis (Go et al., 2009; Colianni et al., 2015). Whether this is due to the complexity of language in the first place, or the high accuracy of words in predicting overall meanings is not fully established.

Once every word was given a score, several other variables had to be created. Due to the growth of the Subreddit in the past few years and the increased distribution of the Bitcoin, data from different timeframes cannot easily be compared. Therefore, I opted for an approach making use of the term frequency-inverse document frequency method (from here on tf-idf). This method assigns a weighting scale to content and is widely used in text mining. In short, tf-idf assigns an importance to a term by comparing it proportionately to the number of times the term is used in a document in a larger corpus (Schütze, 2008). Several different versions of the tf-idf method exist for different data. The best fit for the data at hand, using continuous variables for emotions, appeared to be the basic tf-idf method. The formula used for tf-idf is as follows:

$$\boldsymbol{tf - idf = \frac{f_{t,d}}{T_d} \times \ln\left(\frac{N}{n_t}\right)} \tag{1}$$

Where $f_{t,d}$ represents the number of times a term t appears in a document d, T_d is the total number of terms in a document, N is the total number of documents, and n_t is the number of documents with the term t in it. As the approach of this paper is to create a possible means of analysing emotion with regards to the Bitcoin trading price, it appears feasible to treat each separate day as a single document, and therefore adding up the different emotions for each day. By doing so, the power of daily data was increased due to a larger set of terms for each day, at the cost of reducing the individual data points per individual post.

Further, the tf-idf transformed variables were lagged, as the variable for the value of the bitcoin and that for the transaction volume are both collected from 00:00 at day t coordinated universal time (UTC). The comments on the other hand are collected during a time frame of 00:00 and 23:59 UTC of day t. By not lagging the value of the emotions, the models would therefore show the association between the value of the bitcoin at midnight, and the value of the emotions between midnight of that day and that of the next day. By compiling the emotions into a single variable for a day, the exact timestamp of a comment will be neglected, and only the day at which a comment was made will be used. The lagging of the variable will then serve as a means to find an association between the comments made on day t_{-1} and the value of the bitcoin (or transaction value) on day t.

6.2 – Google Trend Variable

Once the database was created, a specific trend variable was created. This variable is based on the search trends of people using Google. Google makes search preferences publicly available online[10]. However, also here some difficulties had to be overcome. The nature of the platform only allows daily data for a consecutive 90-day period. This means that for the 1461 days of analysis, many searches had to be run and patched together. For every 90-day period, the data is normalised so that the day with the highest search occurrences of the term is given the score of 100, while all other days received a fraction of this score. To make the data comparable, I downloaded each 90-day dataset, with a five-day overlap. For this overlap I calculated the average difference in the scores assigned between the two datasets and used the outcome value as a multiplier for the remaining 85 days in the dataset. This process was repeated until every day within the timeframe of the dataset was transformed. It is important to note that while a Google Trends analysis is always within the range of 1-100, the trend data used here reaches higher values, as later days received more attention than the original value of 100 obtained within the first 90-day window between January and March 2012.

To create a thorough analysis of the data, two models will be conducted. The first one will regard the value of the Bitcoin, while the second analysis tries to find a link between the trading volume of the Bitcoin and the emotions. The analysis of the Bitcoin value will try to find answers regarding hypotheses 1, 2, and 4. The analysis of the Bitcoin trading volume aims to clear up hypothesis 3.

6.3 – The Price Model

In a next step, the dependent variable of the first model will be evaluated. Historically, the Bitcoin price has experienced large degrees of volatility (see Appendix 2 & 3). This is in part since the market itself is the only direct factor giving the currency value, and large shocks like the 2013 demise of the largest Bitcoin trading platform, "Mt. Gox", have a larger impact on the relatively small market. The small size of the market also had adoption rates of platforms accepting the Bitcoin as legal tender pick up over time. The increase in acceptance by more renowned vendors also made it more feasible for people to use the Bitcoin in the first place. Therefore, the dependent variable was transformed to take this into account. Specifically, the first difference of the natural logarithm of the Bitcoin, or simply the log return is used as the dependent variable:

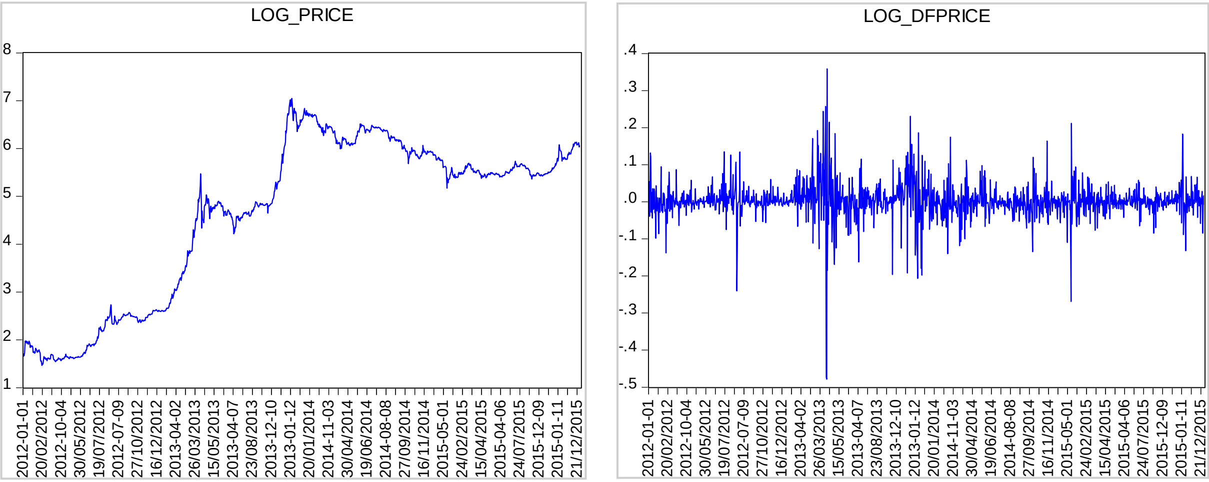
$$\Delta \boldsymbol{ln}(\boldsymbol{y}_{it}) = \boldsymbol{ln}(\boldsymbol{y}_{it}) - \boldsymbol{ln}(\boldsymbol{y}_{it-1}) \tag{2}$$

Where y_{it} is the price of the Bitcoin (in US Dollar terms) on at a given time t. The reason for doing this is the presence of non-stationarity of the Bitcoin price. Furthermore, the first difference of the natural logarithm (FDLN) reduces the skewness and kurtosis of the

[10] Google trends can be accessed through https://www.trends.google.com

variable, strengthens the normal distribution of the regression, and is particularly suitable for time-series models like a GARCH model. By taking the first difference the data will be transformed to show only the change between two days while neglecting the absolute values. The transformation proved effective as a measure to grant stationarity of the variable, which was tested with a unit-root test (see Appendix 4).

Figure 5 – The log transformed price of the bitcoin (left) and the first difference of the log transformed price (right)



The analysis of the price model will be conducted with the use of a special version of the ARCH (Autoregressive Conditional Heteroskedasticity) model. Econometricians have opted for the use of generalised ARCH models, namely GARCH models since these proved to be very robust for financial analyses. However, even models like the GARCH assume that while the markets may experience shocks which affect the volatility of returns, the fluctuation in volatility is not persistent. While there may be times of higher volatility, these will be followed by other times of lower volatility. The underlying structure of the volatility will not be questioned in a GARCH model. However, with a currency as volatile as the Bitcoin, even the GARCH can run into certain difficulties. Due to the relatively small size of the market compared to more conventional financial markets, a strong argument can be made that large shocks may lead to lasting structural changes in the composition of the Bitcoin market. For this, an extension of the GARCH model, the integrated GARCH (IGARCH) model was introduced. The model assumes that shocks in the market will not only have a short-term effect on volatility like the standard GARCH, but that the volatility will be permanently affected by certain shocks.

The IGARCH(1,1) model (see Section 6.5) will therefore be used in the subsequent analysis of the hypotheses. Specifically, a model will be created which tries to serve not only to test the hypotheses, but also as a possible starting point for future research in financial behaviour. The formula for the model used can be seen in equation 3:

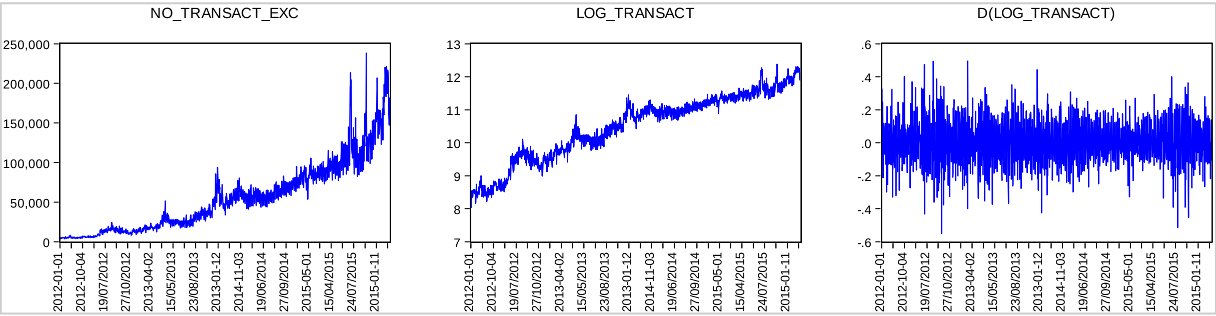
$$R_t = \beta_0 + \beta_1 \, d(\log(price_{-1}) + \beta_2 anticipation_{tfidf\_-1} \times d(\log(price_{-1}) \quad (3)$$
$$+\beta_3 anger_{-1} + \beta_4 anticpation_{-1} + \beta_5 disgust_{-1} + \beta_6 fear_{-1}$$
$$+\beta_7 joy_{-1} + \beta_8 sadness_{-1} + \beta_9 trust_{-1} + \beta_{10} d(Gtrend)$$
$$+ \beta_{11} \max(surprise) + e_i$$

Where R_t is the log return of the Bitcoin price. The Description of the variables can be seen in table 4.

6.4 – The Volume Model

Like the first model, the volume model will also make use of a transformation of the dependent variable. By creating a first difference of log price of the transaction volume the data was made stationary (see Appendix 5). The transformation uses the same formula as the one for the price model (formula 2).

Figure 6 - Transaction value of the bitcoin (left), log transformed (centre), and first difference of log transformation (right)



The second analysis will be based on a similar IGARCH(1,1) as the price model, however using the value of transactions as a proxy for the trading volume. The decision for the use of an IGARCH also stems from the multiple breakpoint test, which indicated the existence of two distinct breakpoints (p=0.000) within the model. The formula for the equation of the volume model can be seen in equation 4:

$$V_t = \beta_0 + \beta_1 \, d(\log(transact_{-1}) + \beta_2 d(\log(m_{cap}) + \beta_3 anger_{-1} \quad (4)$$
$$+\beta_4 disgust_{-1} + \beta_5 fear_{-1} + \beta_6 joy_{-1} + \beta_7 sadness_{-1}$$
$$+ \beta_8 trust_{-1} + \beta_9 d(Gtrend) + \beta_{10} \max(surprise) + e_i$$

Where V_t is the log price for the transaction volume of the Bitcoin. For the description of the entirety of variables used for the price and the volume model, please refer to Table 4.

Table 4 - Table of variables employed and descriptions

Variable	Type	Description
D(log_Price) or R_t	Continuous	FDLN of Bitcoin price
D(log_Transact) or V_t	Continuous	FDLN of Bitcoin transaction value
D(log_m_cap)	Continuous	FDLN of Bitcoin market capitalisation
anger_tfidf	Continuous	Tf-idf transformed variable for anger
anticipation_tfidf	Continuous	Tf-idf transformed variable for anticipation
disgust_tfidf	Continuous	Tf-idf transformed variable for disgust
fear_tfidf	Continuous	Tf-idf transformed variable for fear
joy_tfidf	Continuous	Tf-idf transformed variable for joy
sadness_tfidf	Continuous	Tf-idf transformed variable for sadness
trust_tfidf	Continuous	Tf-idf transformed variable for trust
D(Gtrend)	Continuous	First difference of Google Trend
Max_surprise	Binary	Dummy variable for surprise being the most prominent emotion of a day

6.5 – The IGARCH model

ARCH models, while treating volatility as a time-varying factor, only take the last period's squared residuals into account. As an extension of this, the GARCH model calculates the variance of the next period through both, the last period's squared return, and the last period's forecast (Reider, 2009). As mentioned earlier, this research will make use of the Integrated GARCH model, or IGARCH. The IGARCH is a variant of the conventional GARCH model which further incorporates the persistence of squared shocks. The formula of the IGARCH is

$$\boldsymbol{R_t = \gamma_0 + \gamma_1\sigma_{1,t} + \gamma_2\sigma_{2,t} + \cdots + \gamma_n\sigma_{n,t} + \epsilon_t} \tag{5}$$

$$\boldsymbol{\sigma_t^2 = \alpha_t + (1-\beta_1)\alpha_{t-1}^2 + \beta_1\alpha_{t-1}^2} \tag{6}$$

With,

$$\boldsymbol{\sum_{i=1}^{p}\alpha_i + \sum_{i=1}^{q}\beta_i = 1} \tag{7}$$

Where equation 5 shows the regular mean process of a model for return R at time t with n variables of the ARCH process. Formula 6 is that of the variance equation of the GARCH model where $\alpha_1 + \beta_1 = 1$. Equation 7 shows the variance equation for the IGARCH, which differs from the standard GARCH model in that the sum of alpha and beta are restricted to one, whereas in the standard GARCH model, the sum of alpha and beta is less than one. The specification shown in equation 7 allows the IGARCH to not require stationarity in order for the model to be accurate.

By writing the ARCH(∞), after repeated substitutions, the model is

$$\begin{aligned}\boldsymbol{\sigma_t^2} &= \frac{\boldsymbol{\alpha_0}}{\boldsymbol{1-\beta_1}} + \boldsymbol{\alpha_0}\sum_{\boldsymbol{i=0}}^{\infty} \boldsymbol{\alpha_{t-1-i}^2\,\beta_1^i} \\ &= \boldsymbol{(1-\beta_1)}\sum_{\boldsymbol{i=0}}^{\infty} \boldsymbol{\alpha_{t-1-i}^2\,\beta_1^i} \\ &= \boldsymbol{(1-\beta_1)(\alpha_{t-1}^2 + \beta_1\alpha_{t-2}^2 + \beta_1^2\alpha_{t-3}^2 + \cdots)}\end{aligned} \tag{8}$$

Which shows the exponential smoothing for past squared residuals. The weights of the squared residuals $\boldsymbol{(1-\beta_1), \beta_1(1-\beta_1), \beta_1^2(1-\beta_1), \ldots}$ of the IGARCH sum up to 1, which the model uses as an alternative to the historical variance.

For ARCH, GARCH, and IGARCH processes, the conditional variance is symmetric. This can pose a problem in the models as the models now assume that positive news and negative news have the same effect on the regressor.

The IGARCH is particularly suitable when it is likely that the variance does not only experience changes in volatility, but also breakpoints which cause volatility to change permanently. To test for the existence of permanent structural breaks, the Bai-Perron test will be used (Bai & Perron, 2003). The Bai-Perron test makes use of an algorithm which determines variations from the sum of squared residuals (SSR) to determine multiple unknown breakpoints in the model.

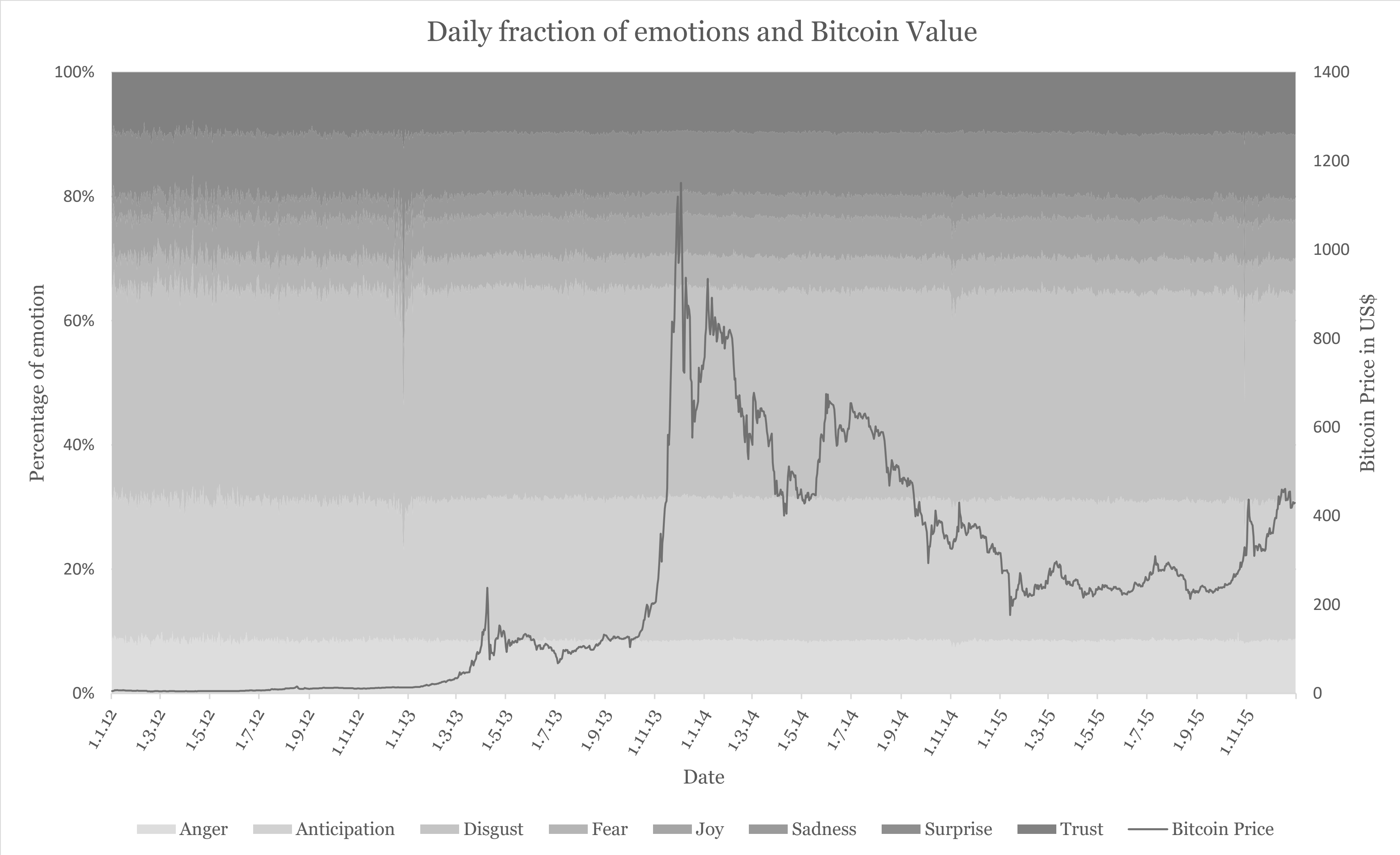
Section 7 – Results

7.1 – Descriptive Statistics

The raw data of emotions depicts a relatively constant level for each emotion. Figure 7 indicates how the different emotions are represented daily. The values for the emotions appear to have a similar value every day, and only show volatility around this point. Especially in the beginning, we can see large volatility, which reduces over time. Disgust (third from below) is shown as the most prominent emotion throughout the timeline, while surprise (third from above) is shown to be the least used emotion. Events that may trigger certain emotions cannot be easily seen in the graph however if the change occurs for only a single day. The graph, however, gives a first overview of the distribution of emotions and the bitcoin price. This distribution does show large differences in how present an emotion is on average.

The graph does not take the tf-idf transformation of the data into consideration. As mentioned before, the tf-idf transformation was necessary to change the weighting of the emotions and make them comparable. Words that are represented more often than others are likely to be over-represented and are less emotionally loaded. As disgust is very over-represented in the raw data analysis of the emotions, it is likely that one or several words which are found to contain degrees of disgust, are likely to be used a lot. The tf-idf transformation takes this into account and reduces the weighting of such words, while strengthening that of others, which occur less often. It is not possible to conduct a similar graph of tf-idf transformed variables, as daily tf-idf values are not strictly positive. Therefore, another means of analysis will be used to analyse the transformed variables, consisting of maximum and minimum graphs and a radar diagram.

Figure 7 - Graph of tractions of emotions and bitcoin price between 2012 and 2015 (see Appendix 6)



The tf-idf transformed data can be viewed below in two distinct histograms. Figure 8 shows the number of times a specific emotion was experienced as the most prominent one of a day. Figure 9 shows the opposite, namely the distribution of the least prominent emotion of a day. While the clustered graph showed disgust as the most prominent emotion for almost every day, the histograms paint a different picture. While disgust is still the most occurring maximum emotion, others show similarly strong attributes. Disgust occurs 361 times as the most prominent emotion, thus making up 24% of all the days, while joy is the most prominent emotion in a day for only 16 times or 1.6% of the entire 1461-day sample.

When comparing the figures for the opposite end of the table, namely the amount of days in which an emotion is the least represented, a different picture unfolds. Apart from trust and anticipation, no other emotion has a significant presence in the figure. Trust itself occurs 783 times as the least prominent emotion within the dataset (53%). Several reasons for this unequal distribution are plausible. Firstly, while the NRC Lexicon lists words and their respective emotions, the interpretation of the emotions stems from human annotators. These had to fulfil the difficult task of assigning emotions to different twitter posts. An emotion like trust may have only been regarded when it was obvious from the posts, and therefore only specific key words which may spark discussions involving the repeated use of the same or similar words have an effect. Some words however may be used regularly and are therefore much more prominent in the dataset. Secondly, as trust is both very prominent in the figure regarding maximum feelings and that regarding minimum feelings, the correctness of the data must not naturally be brought to question. Its strong positive and negative presence could stem from individuals being more prone to use or neglect language that entails trust in specific situations. As mentioned above already, a specific discussion which triggers the continuous argumentation using specific words not commonly used can blur the overall interpretation of an emotion.

Figure 8 - Graph of frequencies of maximum emotions per day

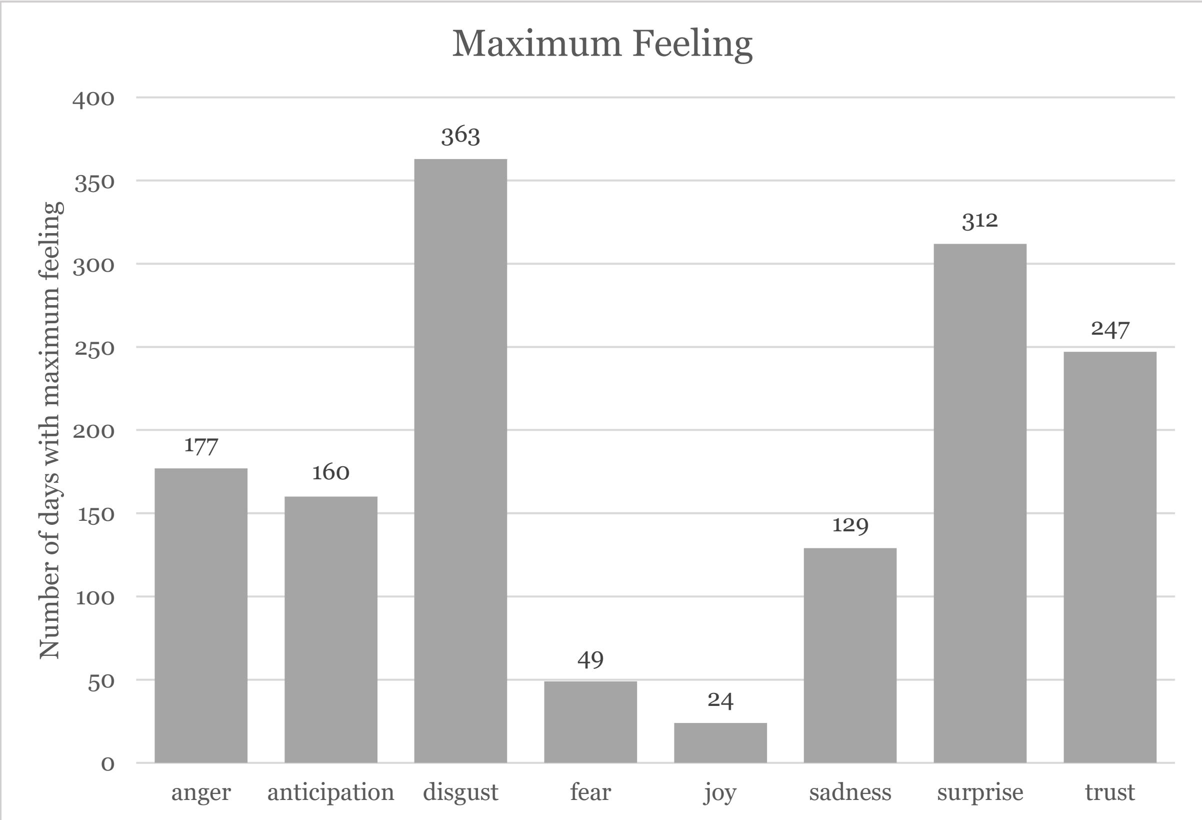
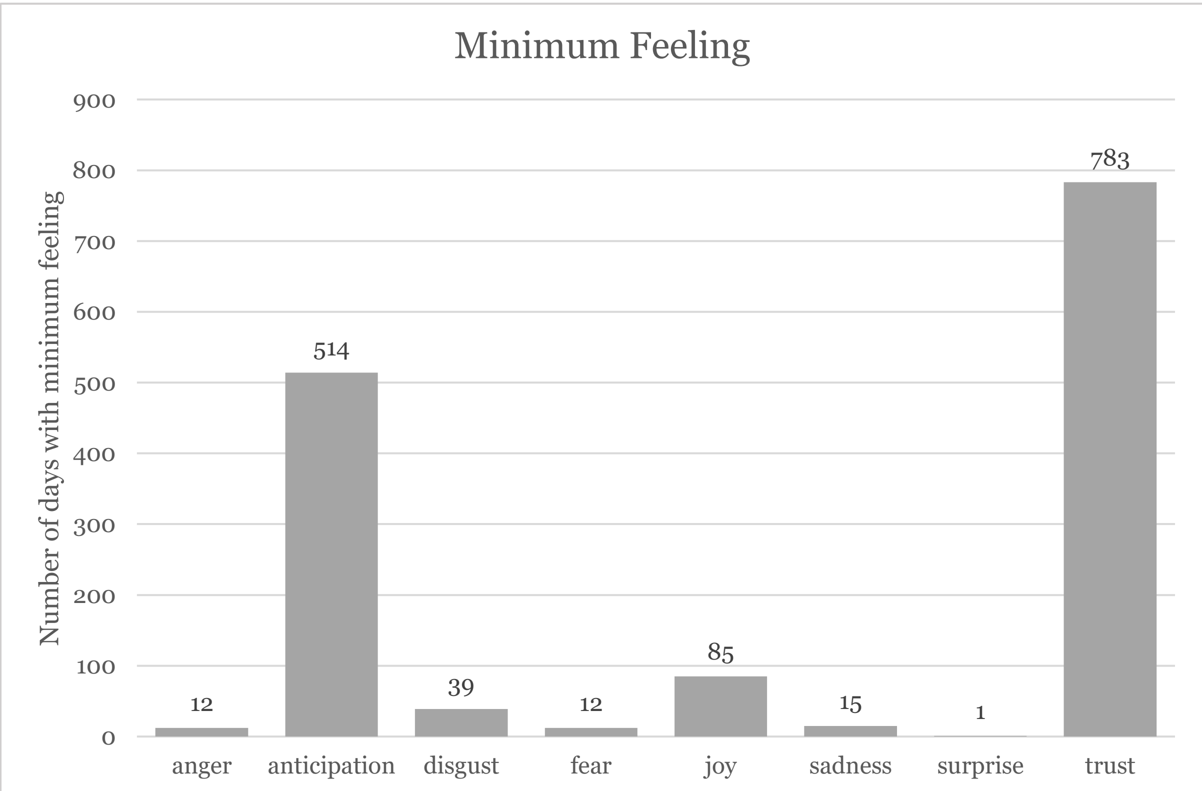
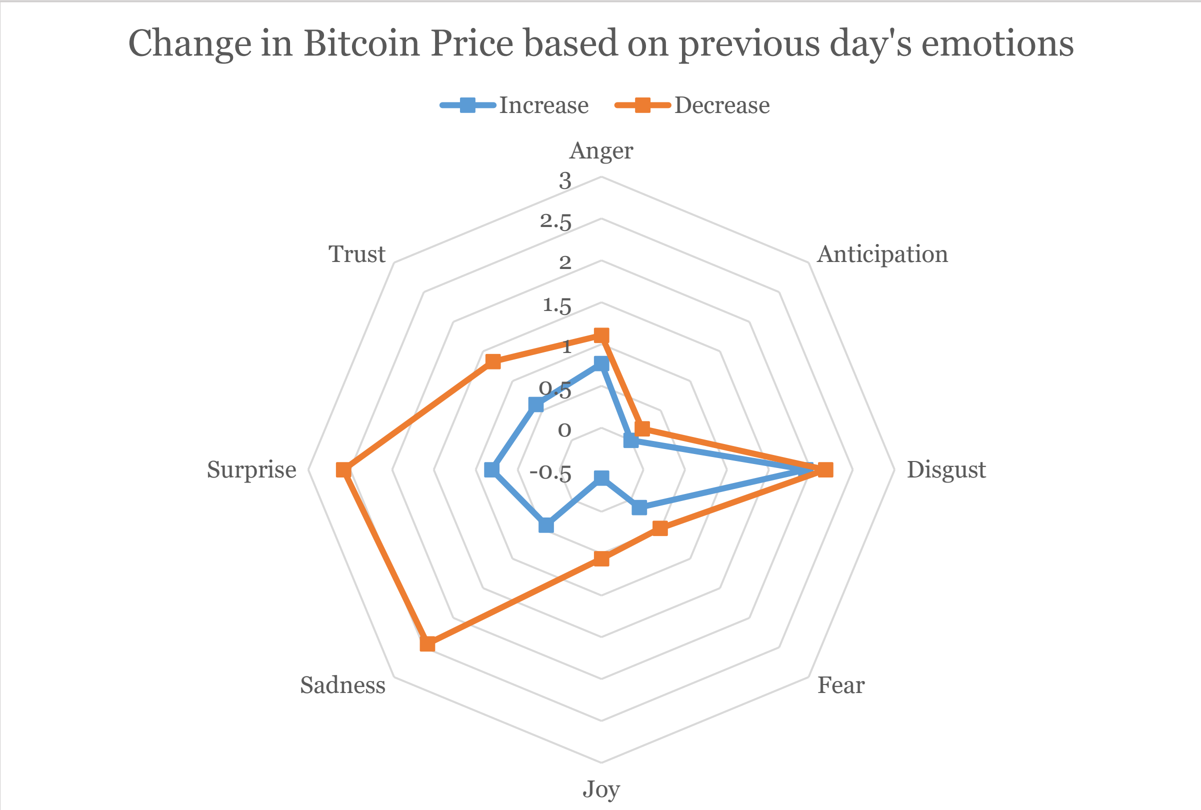


Figure 9 - Graph of frequencies of minimum emotions per day



In a first approach to visualise the emotions in relation to the Bitcoin itself, a radar diagram was created (Figure 10). The diagram depicts the eight emotions used in this paper, and the average tf-idf value for a given day t_{-1}, and the subsequent change in the bitcoin value at time t. The blue line represents the emotions for a subsequent increase in the value of the bitcoin, and the orange line for a decrease. Interestingly, a decrease in the value of the Bitcoin is related to a stronger emotional value on the previous day as compared to an increase in the value for every emotion. However, while anger, anticipation, disgust, and fear show very similar values for increases as well as for decreases in the Bitcoin value, the remaining four emotions do show significant differences in their strength when the value of the Bitcoin is increasing and decreasing. While joy and trust still show moderate differences in the values, especially surprise and sadness create an impression of strong differences leading to a change in the Bitcoin price.

Figure 10 - Radar diagram of average score of emotions for subsequent increase and decrease of bitcoin price



7.2 – Price Analysis

To understand the necessity for an IGARCH, an ARCH test was conducted on the model. The test showed that ARCH effects are indeed present in the model, and therefore the use of a variant of an ARCH model is viable (see Appendix 7). Secondly a multiple breakpoint test was conducted to examine the possibility of structural breaks within the dataset. While a conventional unit-root test is often enough to test for stationarity, these tests fail to take the existence of structural breaks into account. The Bai-Perron breakpoint test with three unknown breaks was used to test for the presence of structural breaks. For all three breaks, the test returned a result which lead to the rejection of the null hypothesis of no structural breaks, and concluded significant breaks at the 5% significance level (see Appendix 8). For this reason, it became viable to use the IGARCH(1,1) model.

The model was built in EViews using the ML – ARCH method to construct an IGARCH(1,1). The IGARCH(1,1) was chosen as both the PACF and the AIC deemed it the superior specification. The AIC can be seen in Table 5 and has a value of -3.689. It should be noted that the number of observations in the model is 1459, as compared to the total of 1461. This is because the first two days were used for the transformation of the variables. The model comprises of a lagged variable for the price, the lagged variable of seven of the eight emotions, an interaction term between anticipation and the lagged price of the Bitcoin, the Google trend variable, and a dummy variable for when surprise was the most prominent emotion present on a day. The full equation for the price model can be seen in equation 7:

$$\begin{aligned}\mathbf{R}_t &= \boldsymbol{\beta}_0 + \boldsymbol{\beta}_1\, \mathbf{d}(\mathbf{log}(\mathbf{price}_{-1}) \\ &+\boldsymbol{\beta}_2 \mathbf{anticipation}_{\mathbf{tfidf}\,_{-1}} \times \mathbf{d}(\mathbf{log}(\mathbf{price}_{-1}) \\ &+\boldsymbol{\beta}_3 \mathbf{anger}_{-1} + \boldsymbol{\beta}_4 \mathbf{anticpation}_{-1} + \boldsymbol{\beta}_5 \mathbf{disgust}_{-1} + \boldsymbol{\beta}_6 \mathbf{fear}_{-1} \\ &+\boldsymbol{\beta}_7 \mathbf{joy}_{-1} + \boldsymbol{\beta}_8 \mathbf{sadness}_{-1} + \boldsymbol{\beta}_9 \mathbf{trust}_{-1} + \boldsymbol{\beta}_{10} \mathbf{d}(\mathbf{Gtrend}) \\ &+ \boldsymbol{\beta}_{11} \mathbf{max}(\mathbf{surprise}) + \boldsymbol{e}_{\mathbf{i}}\end{aligned} \tag{7}$$

Where $\mathbf{R}_t$ is the log return of the bitcoin value, anger, anticipation, disgust, fear, joy, sadness, and trust are the tf-idf transformed variables for seven of the eight emotions, d(Gtrend) is the first difference of the Google Trends variable, and max(surprise) is the dummy variable for surprise.

The first difference of the natural logarithm of the lagged price, which is simply put the lagged difference in the Bitcoin price, is positive with a coefficient of 0.111 and highly significant (P-value 0.000) at the 5% significance level. The model finds strong evidence in a positive relationship between the Bitcoin price and its lagged value. The coefficient of 0.111 (p=0.000) implies a positive relationship between the Bitcoin price at t_{-1} and at time t. An increase in the price of the Bitcoin between t_{-2} and t_{-1} by 1% would lead to a 0.111% increase in the price between time t_{-1} and t. However, this only holds when the variable of anticipation is zero. The lag of the bitcoin value is also used in an interaction term with anticipation. The inclusion of the interaction term makes the main effects of both the lag of the bitcoin value and anticipation misleading. The interaction term looks at how anticipation and the lagged bitcoin value are jointly behaving. It is significant (p=0.010) with a negative coefficient of -0.00645. This implies, ceteris paribus, that an increase in anticipation by one unit will lead to a 0.645% decrease in the bitcoin price. An increase in the value of the bitcoin at time t_{-1} will lead to an ambiguous result at time t, as the main effect is positive while the interaction effect is negative, and will therefore depend on the magnitude of a change in anticipation.

Table 5 - IGARCH(1,1) model for log returns of bitcoin price

Dependent Variable: D(LOG_PRICE)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-8.55E-05	0.000685	-0.124887	0.9006
D(LOG_PRICE(-1))	0.111098	0.020294	5.474478	0.0000***
ANTICIPATION_TFIDF(-1)*D(LOG_PRICE(-1))	-0.006445	0.002506	-2.571544	0.0101**
ANGER_TFIDF(-1)	0.000238	0.000138	1.727990	0.0840*
ANTICIPATION_TFIDF(-1)	0.000109	0.000106	1.025855	0.3050
DISGUST_TFIDF(-1)	-3.06E-06	0.000128	-0.023838	0.9810
FEAR_TFIDF(-1)	-0.000399	0.000604	-0.660581	0.5089
JOY_TFIDF(-1)	0.000143	0.000205	0.697170	0.4857
SADNESS_TFIDF(-1)	-0.000192	0.000542	-0.353879	0.7234
TRUST_TFIDF(-1)	0.000194	7.82E-05	2.479710	0.0131**
D(GTREND)	-8.07E-05	1.59E-05	-5.076146	0.0000***
MAX_SURPRISE(-1)	0.003574	0.001060	3.372673	0.0007***
	Variance Equation			
RESID(-1)^2	0.081889	0.002472	33.12250	0.0000
GARCH(-1)	0.918111	0.002472	371.3558	0.0000

R-squared	0.028216	*Mean dependent var*	0.002987
Adjusted R-squared	0.020828	*S.D. dependent var*	0.048915
S.E. of regression	0.048403	*Akaike info criterion*	-3.689446
Sum squared resid	3.390080	*Schwarz criterion*	-3.642351
Log likelihood	2704.451	*Hannan-Quinn criter.*	-3.671877
Durbin-Watson stat	1.935095		

Hypothesis 2 regarded the special standing of anticipation within the set of emotions analysed in this paper. It argued that "The interaction between anticipation and the value of the Bitcoin is related to the future value of the Bitcoin". The aim of this hypothesis was to examine anticipation's special role as a future-oriented emotion, its implications and method of attaining a result differed greatly from the other emotions. For this reason, the interaction term between the lag of anticipation and the previous value of the bitcoin was used to answer the hypothesis. The significance of the interaction term states that the null of hypothesis 2 must be rejected.

The tf-idf variables for disgust, fear, and joy are all not significant, neither at 5% nor at 10% significance levels. Therefore, they cannot be interpreted. Anger, is significant at the 10%

level (p=0.084) and has a coefficient of 0.00024 which implies that an increase in the tf-idf value of anger by 1 unit will lead to an increase of the Bitcoin price by 0.024%[11]. Trust has a positive coefficient of 0.00019 (p=0.013). The interpretation here is that a 1-unit increase in the lagged variable of trust will cause the Bitcoin price to increase by 0.0194%. The Google trend variable (Gtrend), which was used to capture the interest in the Bitcoin by internet users is also highly significant (p=0.000), but negatively associated with the Bitcoin. When the interest in the Bitcoin increases by 1% between times t and t_{-1}, the Bitcoin price decreases by 0.0081%. As the Gtrend variable depicts the first difference of the trend, the changes in daily interest can be very large, compared to the emotion variables. Therefore, the coefficient of the Gtrend variable is also a lot smaller.

Hypothesis 1, as well as hypotheses 3 and 4 were split into two sections, dealing with different emotions. Hypothesis 1a stated that "anger, joy, and trust lead to an increase in the price of the bitcoin". A rejection of the hypothesis would imply that certain emotions cause the value of the bitcoin to appreciate. While anger was significant at a 10% level, and indicated support towards the rejection of the hypothesis, both joy and trust were not significant. Hypothesis 1b also cannot be rejected. It stated that "disgust, fear, and sadness lead to a decrease in the price of the bitcoin". For all three variables, insignificant results were found, and therefore neither can hypothesis 1b rejected. Overall, the support for a rejection of hypothesis 1a and 1b is weak. The results presented in this paper cannot conclude that the emotions are actively associated with the value of the bitcoin directly.

Lastly, the dummy for surprise was implemented to examine the relationship between the price of the Bitcoin and large degrees of surprise, namely on days when surprise was the most prominent emotion. Similar to anticipation, this variable also had a special standing in the group of the eight emotions discussed in this paper. The coefficient of the surprise dummy was positive with a value of 0.0036, and significant at the 5% significance level (P-value 0.0007). This implies that when surprise is the most prominent emotion of a given day, the value of the bitcoin will increase by 0.36% on the following day.

The surprise dummy was used as a binary variable to test for the impact of large amounts of surprise, in particular, situations in which surprise outperforms all other emotions. As surprise is a subjective emotion, and dependent on how good individuals know the market, in hypothesis 4a, I stated that "large degrees of surprise have an impact on the

[11] As the dependent variable is the first difference of a natural logarithm, as a rule of thumb, for small changes in the independent variable, the dependent variable can be interpreted as a percentage if the coefficient of the independent is multiplied by 100. For anger, the coefficient is 0.00024, therefore the interpretation is a 0.024% increase in the bitcoin value for every unit increase in the tf-idf of anger.

price of the bitcoin". The p-value indicated the variable is significant and therefore the hypothesis is rejected.

The model itself further exemplified through an adjusted R^2 value of 0.0967 indicating that the model can explain roughly 9.67% of the fluctuations within the Bitcoin. The AIC value was the smallest when compared to IGARCH models of other orders.

7.3 – Volume Analysis

For the volume analysis, similar steps as for the price model were undertaken to guarantee the integrity of the model. At first, the model was tested for the existence of ARCH terms (see Appendix 9), thus justifying the use of an ARCH model in the first place. The Bai-Perron breakpoint test for multiple unknown breakpoints further indicated that two distinct breakpoints are present in the data, which was tested at the 5% significance level (see Appendix 10). The model uses a lag of the log return of the transaction volume, a variable for the market capitalisation of the Bitcoin, six emotions as lagged variables (excluding surprise and anticipation), the Google trend variable, and the surprise dummy, like the previous model, and can be seen in Table 6. The full equation for the price model can be seen in equation 8:

$$\begin{aligned} \boldsymbol{V_t} &= \boldsymbol{\beta_0} + \boldsymbol{\beta_1}\,\mathbf{d}(\mathbf{log}(\mathbf{transact}_{-1}) + \boldsymbol{\beta_2}\mathbf{d}(\mathbf{log}(\mathbf{m\_cap}) \\ &+ \boldsymbol{\beta_3}\mathbf{anger}_{-1} + \boldsymbol{\beta_4}\mathbf{disgust}_{-1} + \boldsymbol{\beta_5}\mathbf{fear}_{-1} + \boldsymbol{\beta_6}\mathbf{joy}_{-1} \\ &+ \boldsymbol{\beta_7}\mathbf{sadness}_{-1} + \boldsymbol{\beta_8}\mathbf{trust}_{-1} + \boldsymbol{\beta_9}\mathbf{d}(\mathbf{Gtrend}) + \boldsymbol{\beta_{10}}\mathbf{max}(\mathbf{surprise}) + \boldsymbol{e_i} \end{aligned} \tag{8}$$

Where $\boldsymbol{V_t}$ is the log return of the transaction volume, d(log(m_cap) is the log return of market capitalisation, anger, disgust, fear, joy, sadness, and trust are the tf-idf transformed variables for six of the eight emotions, d(Gtrend) is the first difference of the Google Trends variable, and max(surprise) is the dummy variable for surprise.

The first variable is, similarly to the price model, a lagged variable of the dependent variable, namely the lag of the log returns of total transaction amount of a day. The variable is significant at the 5% significance level (p=0.023) and has the coefficient of -0.496. The implication of this is that an increase in the total transaction volume between time t_{-2} and t_{-1} of 1% will lead to a decrease in the transaction volume between time t_{-1} and t by 0.0496%. Referring to Figure 6, one can see in the left-hand figure that the transaction volume, while increasing over time, follows a pattern of high-days followed by low-days, which can be an explanation for the negative coefficient of the variable.

The next variable in the model, the market capitalisation, had a positive sign with a coefficient of 0.466 and is highly significant at p=0.000. The high significance can be attributed to the strong correlation between the transaction volume and the market capitalisation of financial goods. The variable reads as follows: a 1% increase in the change of market capitalisation of the Bitcoin will lead to a 0.466% increase in the transaction volume of the Bitcoin.

Table 6 - IGARCH(1,1) of FDLN of Bitcoin transaction volume

Dependent Variable: D(LOG_TRANSACT)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.004428	0.003890	1.138220	0.2550
D(LOG_TRANSACT (-1))	-0.049585	0.021860	-2.268284	0.0233*
D(LOG(M_CAP))	0.466180	0.072257	6.451661	0.0000***
ANGER_TFIDF(-1)	-0.000103	0.000740	-0.139066	0.8894
DISGUST_TFIDF(-1)	-0.000265	0.000558	-0.474909	0.6349
FEAR_TFIDF(-1)	0.002735	0.003672	0.744828	0.4564
JOY_TFIDF(-1)	0.000454	0.000957	0.474503	0.6351
SADNESS_TFIDF(-1)	-0.004034	0.003899	-1.034850	0.3007
TRUST_TFIDF(-1)	0.000427	0.000281	1.517607	0.1291
D(GTREND)	0.000618	4.19E-05	14.75713	0.0000***
MAX_SURPRISE(-1)	-0.005568	0.007845	-0.709716	0.4779
	Variance Equation			
RESID(-1)^2	0.033312	0.006152	5.414765	0.0000
GARCH(-1)	0.966688	0.006152	157.1326	0.0000
R-squared	0.101909	*Mean dependent var*		0.002485
Adjusted R-squared	0.095706	*S.D. dependent var*		0.135282
S.E. of regression	0.128645	*Akaike info criterion*		-1.298449
Sum squared resid	23.96378	*Schwarz criterion*		-1.254977
Log likelihood	959.2187	*Hannan-Quinn criter.*		-1.282232
Durbin-Watson stat	2.120274			

Of the six emotions, which were analysed by their tf-idf value, namely anger, disgust, fear, joy, sadness, and trust, none were found to be significant neither at the 5% nor a 10% significance level. This indicates that there is likely to be no relationship between the transaction volume of the Bitcoin and individual's emotions.

Hypothesis 3 was created as the transaction model's counterpart to hypothesis 1. The hypothesis was also split into two parts: hypothesis 3a suggests that "anger, joy, and trust lead to an increase in the trading volume of the bitcoin". In the model, all three variables are found to be insignificant (p=0.889, p= 0.635, and p=0.129, respectively). Therefore, hypothesis 3a cannot be rejected. Hypothesis 3b made use of the remaining three emotions and stated that "disgust, fear, and sadness lead to a decrease in the trading volume of the bitcoin". As like hypothesis 3a, hypothesis 3b cannot be rejected as all three variables it contains are not significant.

The surprise dummy was also used in the volume model to analyse the effect of surprise on the amount of bitcoin trading. A significance of the variable would indicate that surprise, experienced by the bitcoin community, would cause a positive or negative change in the transaction volume of the bitcoin depending on the sign of the coefficient of the variable. However, the dummy shows no significance neither at the 5% nor the 10% significance level.

Hypothesis 4b argued that "large degrees of surprise have an impact on the trading volume of the Bitcoin". As discussed earlier, the variable is defined as a dummy for surprise being the most prominent emotion of a day. No significance was found (p=0.478). Therefore, the hypothesis cannot be rejected. Surprise appears to have no impact on the trading volume of the bitcoin.

As well as in the previous model, the Google trend variable is also significant in the volume model (p=0.000). The variable has a coefficient of 0.000618, which indicates that a 1% increase in the trend between t and t_{-1} will lead to a corresponding increase in the transaction volume of the Bitcoin by 0.062%.

The model itself has an adjusted R^2 value of 0.0957 thus indicating that it can explain around 9.57% of the changes in the transaction volume of the Bitcoin. The model was chosen as it was the most stable one per the PACF and the AIC. However, the emotions do not seem to have a profound impact on the transaction volume of the Bitcoin. A more thorough explanation of this will follow in the discussion section.

7.4 – Forecasting with the Models

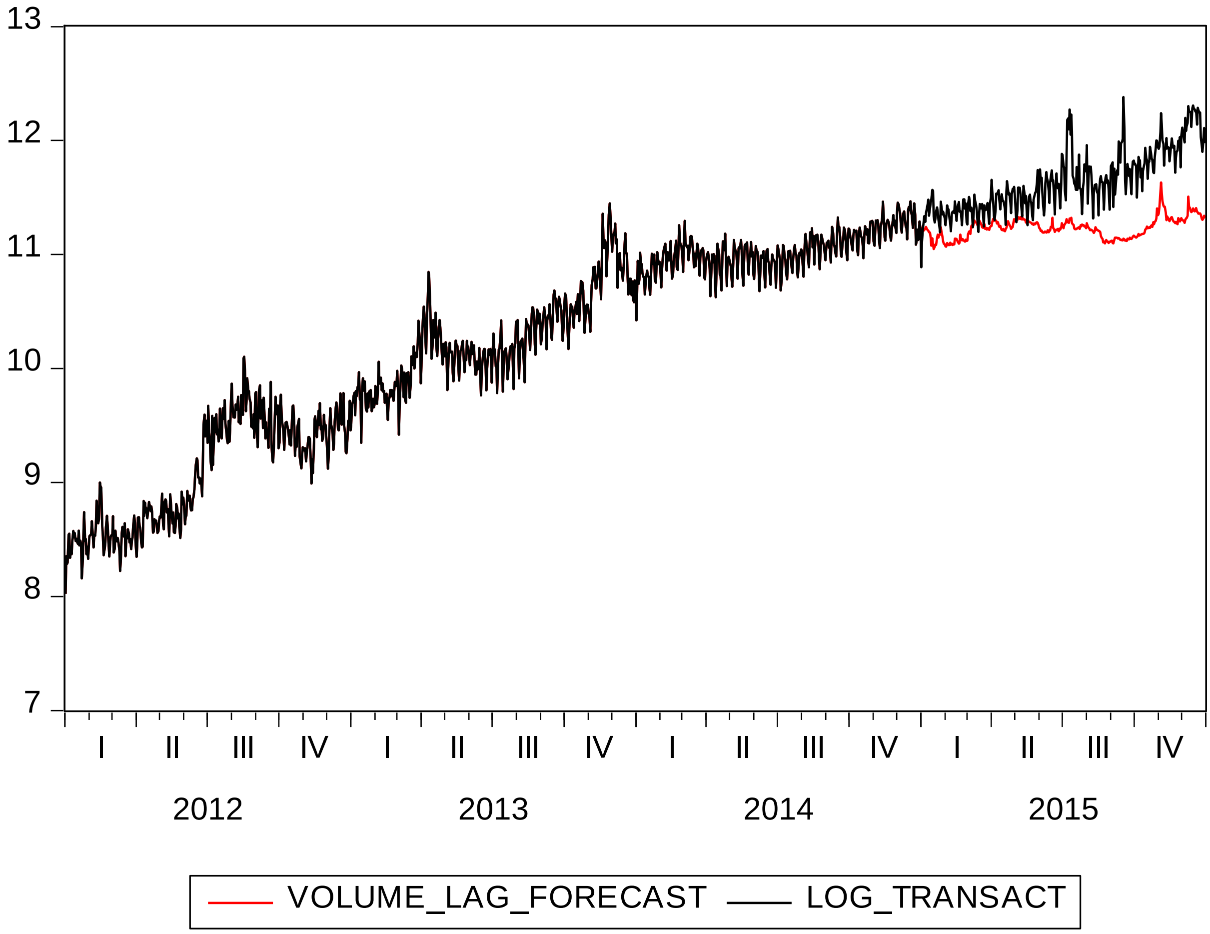
To test the potency of both models, a forecast was created based on the data ranging from 01.01.2012 until 31.12.2014 to test the model against the actual data from 2015. The forecasts were done in EViews, as were the models using the built-in dynamic forecasting feature. The resulting graphs show the forecast as the natural logarithm instead of the first differenced log returns. EViews makes use of the entire model from 2012 until 2014 to then predict the value of the dependent variable (the value of the transaction value) based on the actual independent variables from 2015.

The first forecast shows that of the price model, which can be seen in Figure 11. The black line indicates the actual price movements of the Bitcoin in logarithmic transformation, and the red line shows the price model's prediction of the Bitcoin price over 2015. Overall, the forecast is much less dynamic than the actual price fluctuations and assumes a lower volatility for 2015. However, the slopes of the two models appear to be similar. As the forecast was fed using data from an early timeframe in which the Bitcoin appreciated significantly, the more positive forecast appears reasonable. For a narrower timeframe regarding the forecast for the year 2015, please refer to Appendix 11.

Figure 11 – Log transformed Bitcoin price (black) and forecast for 2015 based on the price model (red)

The graph for the comparison of the volume model and its forecast for 2015 can be seen in Figure 12. Again, the actual data is in black, and the forecast is depicted in red. At first glance, one can see that the day-to-day volatility of the transaction volume is larger than that for the price model. Days with large transaction volumes are followed by ones with lower figures. This volatility is likely to exist due to the nature of the transaction volume which experiences large day-to-day volatility in the first place. Overall the trend for the transaction volume is also positive throughout the timeframe of the analysis. The forecasted model for 2015 shows a less volatile environment, and a stagnating graph. Especially the two outbreaks in mid-2015 were not foreseen by the model. Also, as opposed to the price model forecast, the forecasted bitcoin volume is lower than the actual volume trend. Appendix 12 shows the forecast for the year 2015 alone.

Figure 12 – Log transformed Bitcoin transaction volume (black) and forecast for 2015 based on the volume model (red)



Section 8 – Discussion

8.1 – General Discussion

The two models created to test the impact of emotions on the Bitcoin depict a lack of evidence for the existence of such a relationship. While indeed some impact on emotions could be assessed, the overall hypotheses remain largely unanswered. Four distinct hypotheses were created based on scientific literature. Each hypothesis was aimed at a specific emotion or set of emotions. Overall, neither model fared very well with the data. While the price model did indeed find a relationship, even though weak, between the value of the bitcoin and the variable for anger, as well as significance for surprise and anticipation, the remaining five emotions remained insignificant entirely. The volume model did not find a significance for any of the seven emotions used in the model.

The descriptive statistics of the emotions already revealed how the emotions compare amongst one another. Figures 8 and 9 showed the maximum and minimum occurrences of the emotions. The main findings here were that the spread of the emotions is very uneven. Particularly for the least common emotion on a day, two emotions, namely anticipation and trust, stuck out as having a much larger representation in the graph than all other emotions. While the graph for the maximum emotions showed a more equal distribution, joy and fear appeared to be underrepresented. The deeper implications of these figures could be a misrepresentation of the emotions. While the NRC EmoLex is a vast database, and one of the most comprehensive ones available, its ability to make comprehensive claims for more than single words may be lacking compared to more complete approaches of sentiment analysis like computer learning algorithms. Thus, the emotions analysed here may not be able to tell the full story of the underlying emotions regarding individual posts and comments.

While the emotions were further transformed using the term frequency - inverse document frequency approach, which tries to assert a term's importance relative to others in a dataset, the context of a word within a sentence can vary vastly depending on the topic. Other variables, like the Google Trend variable appear to be crucial in giving the model more explanatory power. However, while the models were not able to find a meaningful and significant relationship between emotions and the Bitcoin, an introduction into the topic was made. Especially microblogging service *twitter* has in the recent past received a lot of attention from data scientists and researchers from other fields alike. The restriction of 140 characters and the impersonal way of discussion between individuals shows clear disadvantages towards other platforms for personal exchange like the Reddit.

The question of whether it is indeed already possible to make assertions regarding the Bitcoin in the first place should also be addressed. The currency is still in its infancy. Nearly on a bi-annual basis, the community is exposed to large shocks often related to large-scale theft or other fraudulent behaviour often associated with Bitcoin exchanges. Furthermore, the lack of official oversight of the Bitcoin by an independent institution will continue to make the Bitcoin extremely volatile compared to most national currencies. This high volatility makes it very difficult to trade the Bitcoin like a currency, and perhaps more like a risky stock.

8.2 – Implications

One could see that working with emotions in the context of online comments is a rather complicated endeavour. Both, the Reddit database and the Bitcoin itself are still very young. The difficulties associated in working with these datasets were documented carefully in this thesis. Three main concerns emerged from this: either the short timeframe which was used in this paper is indeed not enough to capture the association between emotions and a cryptocurrency market, the emotions mapped in this thesis were too simplistic to find meaningful results, or the market is not strongly affected by emotions in the first place.

Firstly, the study of emotions in the context of online comments is an interesting new approach of gathering first-hand resources. The extremely vast Reddit corpus can become an important research tool for academics all over the world. Just as twitter is currently used by a multitude of research papers regarding sentiment, the Reddit corpus can add even more depth to this. In this paper, by using the NRC EmoLex, I was able to create models based on a Lexicon approach of sentiment analysis. This approach had its positive aspects, however negative ones should also be mentioned. Section 7.1 analysed the emotions more closely in a descriptive analysis and came to the conclusion that the emotions are very unevenly distributed. This could imply that the specification of emotions requires more resources to make the emotional lexicon better.

Secondly, the results shown in this study can be ambiguous if taken out of context. While the model in Table 5 did indeed show significant results, the implications of those are more difficult to understand than one may be aware off at first sight. While the continuous variables were generally not significant, even significance would have been difficult to explain due to the necessary tf-idf analysis. For anger, which proved to be significant at the 10% significance level in the price model, no exact implications can be made, as the value of the coefficient depends also on the tf-idf formula introduced in equation 1. Both anticipation and surprise were significant in this model as well, however these emotions are unpredictable entirely. Anticipation regards the gamble for the future, while surprise relates to an effect which can only be seen in hindsight. The second model (Table 6), shows indicates no statistically significant between the transaction volume and emotions at all. Therefore, even the results about the value of the bitcoin must be interpreted with caution. While the price of the bitcoin may indeed be affected by certain emotions, the amount of trading seems to be unaffected by this, which appears to be a paradox.

Finally, while the results of this study may not readily lead to a conclusion that emotions and financial systems are intertwined, no such assertion can be made from the results either. In fact, the methodological approach could be refined to broaden the scope of this research. I believe that the predictability of emotions could be enhanced if a more sophisticated approach would be taken (see section 8.4). However, due to a limit of time and resources, this was not possible in this paper.

8.3 – Limitations

This study tried to venture into a new territory, namely to use the young field of data science and combine it with a vast dataset. The work on such an extensive field encompassing several academic and practical fields is challenging but the outcomes can be interesting to say the least. Therefore, some limitations should be addressed.

The main limitation of this paper is first and foremost the approach to data mining applied. This thesis was written as a trade-off between in-depth data mining and while more in-depth methods of emotion and sentiment analysis exist, leading into machine learning capabilities, these are however well beyond the scope and the scale of this paper. The approach of using a comprehensive existing lexicon and applying it to a platform like the Reddit should be regarded as an introduction into the possibility of conducting quantitative research on the platform than a state-of-the-art methodology. With a limited timeframe and close to no prior knowledge in R, Python, C#, and other applications used in this study, a lot of time (and many long nights) went into acquiring these skills and applying them to the best of my ability.

Another limitation may be the Bitcoin itself. As a cryptocurrency, the Bitcoin shares most properties of real currencies, however the means of creating Bitcoins can pose several problems. During the timeframe that this paper deals with (2012-2015), more than 5.5-million or 25% of Bitcoins were mined, which would be considered a state of hyperinflation for normal currencies. The mining of Bitcoins becomes more difficult with fewer being left to mine. The vast increase in the number of Bitcoins also has implications on the price and the transaction value of the Bitcoin, which cannot be quantified entirely as not every bitcoin in existence is also a bitcoin in circulation.

Furthermore, the timeframe of this research could be considered another limitation. Specifically, the age of the Bitcoin and the Bitcoin-related Subreddits. As both are less than 8 years old, and internet usage is still rising rapidly around the world, so is the demand for the Bitcoin rising and the participation in the Subreddit. These two effects cannot be ignored. A replication of this research utilising data from a timeframe from 2015-2018 may already find completely different results. The volatility of the Bitcoin, while reducing in past months is still a very real problem for a comprehensive analysis of the cryptocurrency as such. Until the market is more stable, vendors are more established, and problems regarding fraudulent Bitcoin trading services are minimised, the volatility of the Bitcoin will likely remain high however.

8.4 – Recommendations for Future Research

In writing this paper, several obstacles had to be overcome, while others were too large to tackle. Therefore, I would like to portray certain recommendations for future research regarding the Bitcoin, Reddit, and sentiment analysis as a whole.

Firstly, the Bitcoin is a young and unproven cryptocurrency, which is still not taken very serious in the financial world. However, like PayPal has slowly changed the way we conduct online transactions, cryptocurrencies may become a feasible and legitimate means of conducting business in the future. Therefore, economists should expand their research on the financial markets to also include cryptocurrencies in their analyses. Understanding possible differences and similarities between these digital currencies and our real currencies may bring about great benefit in the future. Especially, since more and more of our everyday transactions already occur online, or at least through bank- and credit cards.

The Reddit corpus is still unproven ground for research. While not being available for long yet, it may perhaps already be one of the most comprehensive databases regarding human interaction. Through constant updates towards the database, the data is always timely. The use of subreddits, can also bring about great benefit to researchers, as the data is already sorted by specific categories. Further research based on the Reddit database may likely bring about great new insights for behavioural sciences and the academic community as a whole.

Lastly, sentiment analyses are an interesting and elegant approach to understanding human behaviour better. Especially theories regarding stated and revealed preferences come to mind when making analyses related to emotions on forums. Future research could explore the link between written text as a stated preference and subsequent changes in the markets as revealed preferences. Also, research in the field of intertemporal choice, risk and uncertainty, social preferences, and heuristics and biases could be extended through sentiment analysis.

Section 9 – Conclusion

The aim of this study was to find a relationship between emotions and the Bitcoin using a previously disregarded database. For this, a lexicon-based analysis using data from the popular discussion platform Reddit was used. Due to the internet, and the ever-growing population of individuals being able to use it, big-data is now a form of analysis that can be conducted by everyone with the right tools. The ability to capture and make use of the digital world we live in can bring about large-scale improvements in the way we understand our people, and through them our economy. While this thesis was aimed at only a small, and insignificant digital currency in comparison to the global financial market, the possibility of expanding the scale and scope does exist.

While the results presented in this paper are overall not significant, they do however serve as a means of showcasing the possibilities the scientific community has today. Behavioural sciences are currently revolutionising economics as we have known it. Through the use of new theories, the status quo, which was micro- and macroeconomic policy based on unrealistic assumptions may not be doomed, however through the use of new tools and by developing a greater understanding of irrationality, the existing theories can be greatly improved.

While the results presented in this paper do not paint a coherent picture, they can nevertheless be regarded as an interesting argument for greater emphasis on sentiment analysis as a whole. While the results of this paper were unable to attest a holistic relationship between the Bitcoin and emotions, further research in the domain of emotion analysis should be conducted to broaden our understanding of the interplay of human emotions and their subsequent actions. For this matter, the research question which I was trying to answer "*How do emotions impact financial markets such as the Bitcoin market?"* cannot be answered in a comprehensive manner.

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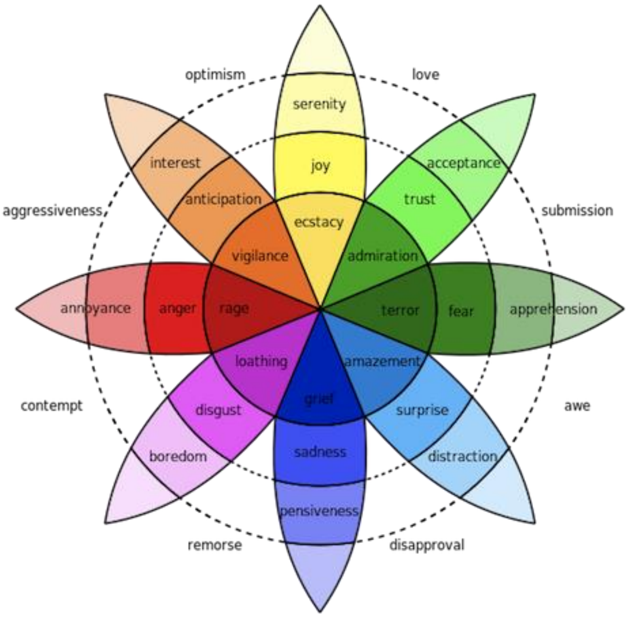
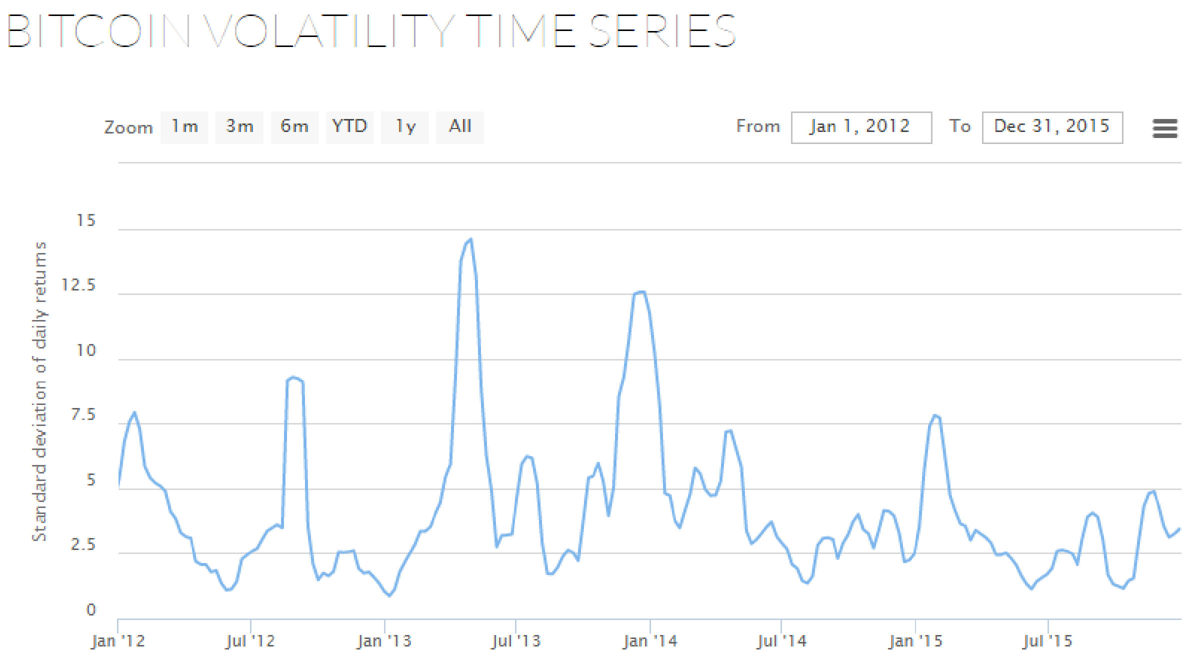
Appendix

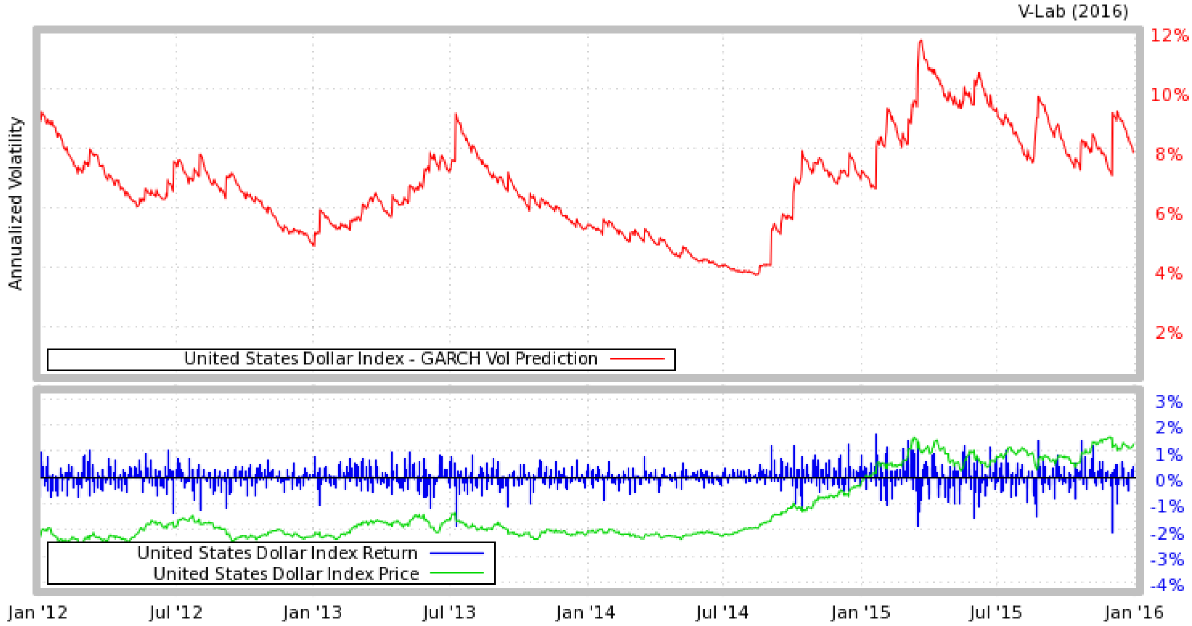
Appendix 1: Plutchik's Wheel of emotions describes our eight basic emotions and all their derivatives and interactions



Appendix 2: Volatility of Bitcoin Price between 2012 and 2015. Comparing this to Appendix 3, one can see that the bitcoin does not only experience a larger range of volatility, but also many short-lived peaks.



Appendix 3: Volatility of the US Dollar between 2012 and 2015. Compared to the Bitcoin, the US Dollar shows less volatility.



Appendix 4: Unit-Root test for the FDLN of the bitcoin price. P-value of 0.000 indicates that the null hypothesis of a unit root is rejected and the variable is stationary.

Null Hypothesis: D(LOG_PRICE) has a unit root
Lag Length: 0 (Automatic - based on SIC, maxlag=16)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-19.12727	0.0000
Test critical values:	1% level	-3.448062	
	5% level	-2.869241	
	10% level	-2.570940	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(LOG_PRICE,2)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(LOG_PRICE(-1))	-1.003745	0.052477	-19.12727	0.0000
C	0.000831	0.001888	0.440037	0.6602

R-squared	0.501957	Mean dependent var	-2.89E-05
Adjusted R-squared	0.500585	S.D. dependent var	0.051029
S.E. of regression	0.036062	Akaike info criterion	-3.801680
Sum squared resid	0.472074	Schwarz criterion	-3.780311
Log likelihood	695.8066	Hannan-Quinn criter.	-3.793188
F-statistic	365.8523	Durbin-Watson stat	2.000364
Prob(F-statistic)	0.000000		

Appendix 5: Unit Root test for the FDLN of the bitcoin transaction volume. P-value of 0.000 indicates that the null hypothesis of a unit root is rejected and stationarity is present.

Null Hypothesis: D(LOG_TRANSACT) has a unit root
Lag Length: 6 (Automatic - based on SIC, maxlag=16)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-8.516680	0.0000
Test critical values:	1% level	-3.448062	
	5% level	-2.869241	
	10% level	-2.570940	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(LOG_TRANSACT,2)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(LOG_TRANSACT(-1))	-2.066846	0.242682	-8.516680	0.0000
D(LOG_TRANSACT(-1),2)	0.802925	0.215652	3.723250	0.0002
D(LOG_TRANSACT(-2),2)	0.491758	0.184227	2.669304	0.0079
D(LOG_TRANSACT(-3),2)	0.297556	0.150363	1.978920	0.0486
D(LOG_TRANSACT(-4),2)	-0.003662	0.118712	-0.030848	0.9754
D(LOG_TRANSACT(-5),2)	-0.189577	0.083832	-2.261405	0.0243
D(LOG_TRANSACT(-6),2)	-0.281850	0.050841	-5.543793	0.0000
C	0.004425	0.005714	0.774393	0.4392

R-squared	0.678417	Mean dependent var	-9.25E-05
Adjusted R-squared	0.672111	S.D. dependent var	0.189732
S.E. of regression	0.108644	Akaike info criterion	-1.579810
Sum squared resid	4.213840	Schwarz criterion	-1.494333
Log likelihood	296.3154	Hannan-Quinn criter.	-1.545841
F-statistic	107.5904	Durbin-Watson stat	1.982556
Prob(F-statistic)	0.000000		

Appendix 6: Descriptive Statistics on the first difference of the emotions

	DF_ANGER	DF_ANTICIPATION	DF_DISGUST	DF_FEAR	DF_JOY	DF_SADNESS	DF_SURPRISE	DF_TRUST
Mean Mean	-0.001234	-0.004680	0.010709	-0.000557	-0.001853	0.001858	0.001918	0.001582
Median Median	-0.010000	0.009050	0.003300	-0.001700	-0.001700	-0.001000	0.002600	-0.013050
Maximum Maximum	33.50400	123.8163	67.41280	26.99947	74.52961	149.4090	130.6284	166.0025
Minimum Minimum	-35.49700	-125.0840	-74.19560	-26.99425	-74.52912	-149.4189	-130.5647	-162.3514
Std. Dev. Std. Dev.	5.945619	11.39499	8.364181	1.585381	5.967681	5.680340	5.217016	15.84957
Skewness Skewness	0.080950	-0.055119	0.099126	-0.124473	0.127154	-0.001102	0.008420	0.014148
Kurtosis Kurtosis	11.81287	33.73783	20.80763	124.2281	84.89816	656.6908	538.8979	27.62190
Jarque-Bera Jarque-Bera	4726.319	57476.94	19293.35	894026.0	408031.9	25994795	17470517	36879.53
Probability Probability	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
Sum Sum	-1.801550	-6.833420	15.63509	-0.812980	-2.705410	2.713110	2.800730	2.309170
Sum Sq. Dev. Sum Sq. Dev.	51576.21	189445.2	102070.9	3667.101	51959.69	47076.48	39709.98	366513.8

Appendix 7: Test for ARCH effects in the price model. P-value is 0.000, implying ARCH effects exist.

Heteroskedasticity Test: ARCH

F-statistic	174.5073	Prob. F(1,1456)	0.0000
Obs*R-squared	156.0444	Prob. Chi-Square(1)	0.0000

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.001436	0.000183	7.831072	0.0000
RESID^2(-1)	0.327159	0.024766	13.21012	0.0000

R-squared	0.107026	Mean dependent var	0.002135
Adjusted R-squared	0.106413	S.D. dependent var	0.007092
S.E. of regression	0.006704	Akaike info criterion	-7.170860
Sum squared resid	0.065438	Schwarz criterion	-7.163610
Log likelihood	5229.557	Hannan-Quinn criter.	-7.168155
F-statistic	174.5073	Durbin-Watson stat	2.146841
Prob(F-statistic)	0.000000		

Appendix 8: Multiple breakpoint test for the price model. 3 significant breakpoints found.

Multiple breakpoint tests
Bai-Perron tests of L+1 vs. L sequentially determined breaks
Breakpoint variables: C D(LOG_PRICE(-1)) D(_ANTICIPATION_TFIDF)*D(LOG_PRICE(-1)) D(_ANGER_TFIDF) D(_ANTICIPATION_TFIDF) D(_DISGUST_TFIDF) D(_FEAR_TFIDF) D(_JOY_TFIDF) D(_SADNESS_TFIDF) D(_TRUST_TFIDF) D(TREND) MAX_SURPRISE(-1)
Break test options: Trimming 0.15, Max. breaks 3, Sig. level 0.05

Sequential F-statistic determined breaks: 3

Break Test	F-statistic	Scaled F-statistic	Critical Value**
0 vs. 1 *	14.50729	174.0875	27.03
1 vs. 2 *	5.296736	63.56084	29.24
2 vs. 3 *	3.564479	42.77375	30.45

* Significant at the 0.05 level.
** Bai-Perron (Econometric Journal, 2003) critical values.

Break dates:

	Sequential	Repartition
1	4/13/2013	4/12/2013
2	12/14/2013	12/14/2013
3	1/18/2015	1/18/2015

Appendix 9: Test for ARCH effects in the volume model. P-value is 0.000, implying ARCH effects exist.

Heteroskedasticity Test: ARCH

F-statistic	26.59996	Prob. F(1,1457)	0.0000
Obs*R-squared	26.15890	Prob. Chi-Square(1)	0.0000

Test Equation:
Dependent Variable: WGT_RESID^2
Method: Least Squares

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.875383	0.047550	18.40962	0.0000
WGT_RESID^2(-1)	0.133849	0.025952	5.157515	0.0000

R-squared	0.017929	Mean dependent var	1.010801
Adjusted R-squared	0.017255	S.D. dependent var	1.527501
S.E. of regression	1.514265	Akaike info criterion	3.669108
Sum squared resid	3340.900	Schwarz criterion	3.676353
Log likelihood	-2674.614	Hannan-Quinn criter.	3.671810
F-statistic	26.59996	Durbin-Watson stat	1.995223
Prob(F-statistic)	0.000000		

Appendix 10: Multiple breakpoint test for the volume model. 3 significant breakpoints found

Multiple breakpoint tests
Bai-Perron tests of L+1 vs. L sequentially determined breaks
Date: 10/14/16 Time: 19:51
Sample: 1/01/2012 12/31/2015
Included observations: 1459
Breakpoint variables: C D(LOG(NO_TRANSACT_EXC(-1)))
D(LOG(M_CAP)) D(_ANGER_TFIDF) D(_DISGUST_TFIDF)
D(_FEAR_TFIDF) D(_JOY_TFIDF) D(_SADNESS_TFIDF)
D(_TRUST_TFIDF) D(TREND) MAX_SURPRISE(-1)
Break test options: Trimming 0.15, Max. breaks 3, Sig. level 0.05

Sequential F-statistic determined breaks: 2

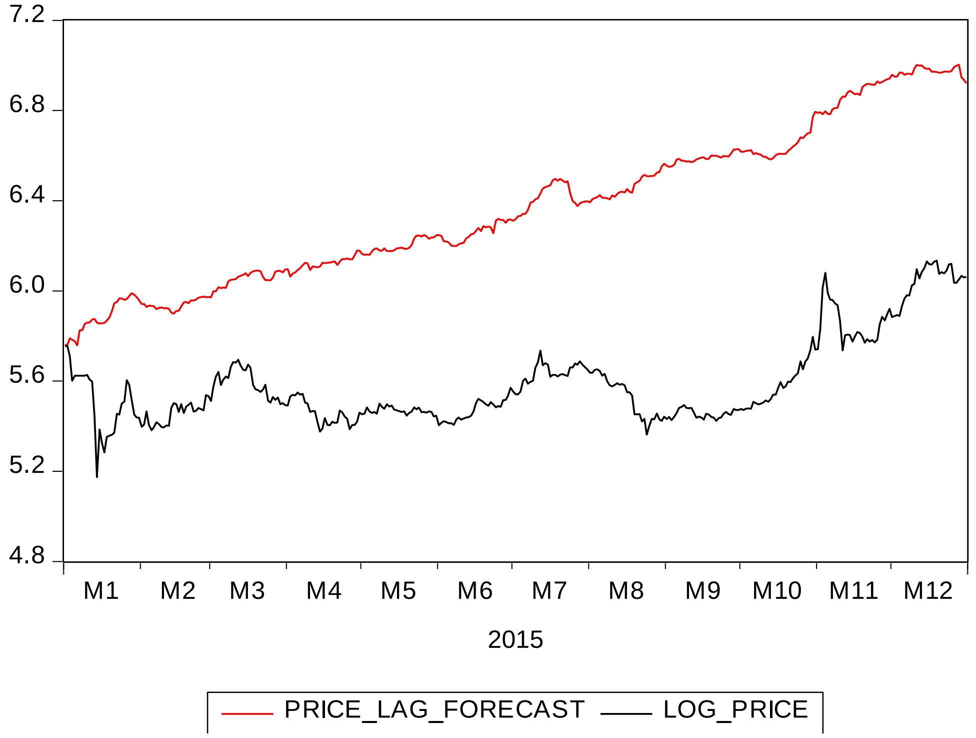
Break Test	F-statistic	Scaled F-statistic	Critical Value**
0 vs. 1 *	3.663951	40.30346	27.03
1 vs. 2 *	2.694478	29.63926	29.24
2 vs. 3	1.654690	18.20159	30.45

* Significant at the 0.05 level.
** Bai-Perron (Econometric Journal, 2003) critical values.

Break dates:

	Sequential	Repartition
1	4/07/2013	4/07/2013
2	3/09/2014	3/09/2014

Appendix 11: Forecast and actual Bitcoin price (log transformed) with the Price model between January and December 2015



Appendix 12: Forecast and actual Bitcoin transaction volume (log transformed) with the Bitcoin transaction volume model between January and December 2015