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Sentiment and Feedback Trading in Bitcoin Markets

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Contents

List of Figures ... 3

List of Tables ... 3

Abstract ... 4

1. Introduction ... 5

2. Research Scope ... 6

2.1 Research Gap ... 6

2.2 Purpose and Research Questions ... 7

2.3 Delimitation ... 8

3. Background – Bitcoin and The Blockchain ... 8

4. How to Classify Cryptocurrencies? ... 11

4.1 Bitcoin as a Currency ... 11

4.2 Bitcoin as an Asset ... 13

5. Bubble Mechanics ... 14

5.1. The Emergence of Financial Bubbles ... 14

5.2 Speculative Bubbles: Rational and Irrational ... 16

5.3. Speculative Bubbles in Cryptocurrency Markets and the Fundamental Value of Bitcoin ... 16

6. Sentiment and Positive Feedback ... 19

6.1. Rational and Irrational Traders ... 20

6.2. Sentiment in Financial Markets ... 21

6.2.1. Theoretical Effects of Sentiment on Prices ... 22

6.2.2. Approaches to Sentiment ... 23

6.2.3. Sentiment and Bitcoin ... 26

6.3. Feedback Trading ... 27

6.3.1. Feedback Traders ... 28

6.3.2. Previous Research on Autocorrelation in Stock Returns ... 29

6.3.3. Feedback Trading and Bitcoin ... 29

6.4. On the Link Between Feedback Trading and Sentiment ... 30

7. Analysis of the Bitcoin Market ... 31

7.1. New Era Thinking ... 31

7.2. The Effect of Massive Social Media and the Internet ... 34

7.3. Regulation ... 36

7.4. Trust ... 40

8. Methodology ... 41

8.1. Research Methodology ... 41

8.1.1 Research Philosophy ... 41

8.1.2 Research Approach 42
8.1.3 Research Strategy 43
8.1.4 Method Choice 44
8.1.5 Time Horizons 44
8.2. Sentiment Index 44
8.2.1. Data Presentation and Variables 45
8.2.2. Composite Index Construction 52
8.3. Sentiment and Feedback Trading Model 55
8.3.1 Data Description 55
8.3.2 Feedback Trading Model (Sentana and Wadhwani) 56
8.3.3 Feedback Trading with Sentiment 59
8.3.4 Parameter Fitting 62
9. Empirical Results 66
9.1. Empirical Results (Sentiment Index) 66
9.2. Empirical Results (Feedback Trading Models) 71
10. Discussion 78
10.1. Serial Correlation of Returns in Bitcoin Markets 79
10.2. Influence of Sentiment on the Serial Correlation of Returns 82
10.3. Contributions to Literature 83
10.4. Limitations 84
10.4.1. Limitations Related to the Sentiment Indices 84
10.4.2. Limitations Related to the Feedback Trading Models 86
10.5. Future Research 87
11. Conclusion 88
Appendix ii
Bibliography v

List of Figures and Tables

List of Figures

Figure 1 – Total number of transactions in Bitcoin ... 9
Figure 2 - Theoretical Effects of Investor Sentiment on Different Types of Stocks ... 23
Figure 3 – Total number and dollar volume of monthly ICOs ... 33
Figure 4 – UBIA and BTSC ... 34
Figure 5 - turn ... 46
Figure 6 - pdnd ... 48
Figure 7 - cefd ... 49
Figure 8 - s ... 50
Figure 9 - nipo ... 51
Figure 10 - ripo ... 51
Figure 11 – Bitcoin Price ... 56
Figure 12 – Bitcoin Daily Return ... 56
Figure 13 - SENTIMENT ... 68
Figure 14 – SENTIMENT^ ... 69
Figure 15 – SENTIMENT^ vs NYSE Composite Index ... 71
Figure 16 - Bitcoin Daily Returns Volatility ... 73
Figure 17 - Implied Autocorrelation of Returns ... 78

List of Tables

Table 1 - Correlation of variables with first stage indices ... 67
Table 2 - Summary Statistics (SENTIMENT and SENTIMENT^) ... 69
Table 3 - Comparison of GARCH Models ... 72
Table 4 - Parameter Calibration (SENTIMENT) ... 75
Table 5 - Parameter Calibration (SENTIMENT^) ... 76

Abstract

With the increasing research on behavioural economics in recent years, the topics of feedback trading and sentiment have received considerable attention. Previous research on feedback trading proposed various models for the behaviour of investors in financial markets. The relationship between volatility and feedback trading, usually recognized through serial correlation of stock returns, has been well investigated. Given the growing exposition of Bitcoin to financial activity and the considerable fluctuation of its prices, it represents a key opportunity to study investor sentiment and feedback trading and their relationship to volatility.

Research on feedback trading is scarce as Bitcoin markets are still evolving and subject to changing dynamics. Our ambition is to advance the understanding of investor behaviour in Bitcoin markets with respect to feedback trading and investor sentiment. We investigate the serial correlation of returns and examine its relationship with conditional volatility and sentiment. We apply Sentana and Wadhwani's (1992) feedback trading model and the extensions proposed by Chau et al. (2011) that allow for sentiment. To proxy for investor sentiment, we calculate the Baker and Wurgler (2006) investor sentiment index.

We find that with increasing volatility, the prominence of positive feedback trading also increases in Bitcoin markets which is consistent with Sentana and Wadhwani's (1992) findings in stock markets. In contrast, for low levels of volatility, the presence of positive feedback trading is smaller and Bitcoin returns are positively correlated. Our main findings are this inverse relationship between serial correlation of returns and volatility, as well as a predominance of positive autocorrelation in returns.

When analysing the impact of U.S. investors' sentiment in feedback trading in Bitcoin markets, our results are ambiguous and inconclusive. The reason for this is rooted in the difficulty in replicating the index constructed by Baker and Wurgler (2006) and the intrinsic difficulty of measuring investor sentiment in Bitcoin markets. Nonetheless, the results obtained in our analysis further the understanding of positive feedback trading, volatility, and sentiment in Bitcoin markets.

1. Introduction

Paul Samuelson, one of the most decorated economists of all time, aptly emphasised the relevance of research investigating financial crises by stating “what we know about the global financial crisis is that we don't know very much”. Throughout the past decade, triggered by the financial events of 2008 and 2009, more and more research focussed on the dynamics of financial crises. Particularly, an increasing number of researchers has acknowledged the role of speculative bubbles in the materialisation of financial crises. At present, research identifies two broad categories of determining factors that pave the way for speculative bubbles: fragile financial systems and factors of irrational behaviour in financial markets, such as herding and feedback trading.

Previous research on feedback trading proposed models that yield different implications for the autocorrelation patterns of financial time series (Cutler, Poterba, & Summers, 1990; Shiller R. J., 1984; Sentana & Wadhwani, 1992). These models, however, focus on symptoms of positive feedback trading in stock market indices, which are difficult to draw conclusions from as these indices are not traded directly but reflect upon the existence of feedback trading of the underlying stocks. In contrast, Chau et al. (2011) analysed the existence of positive feedback trading in Exchange Traded Funds, allowing direct observation of positive feedback behaviour and its link to volatility.

The cryptocurrency market is another particularly interesting case in research on speculative bubbles and irrational behaviour as it is still emerging and not affected by a myriad of regulations. With the extreme growth and subsequent decline of Bitcoin prices in late 2017, early 2018, the debate about whether Bitcoin markets exhibit signs of speculative bubbles intensified. The scarcity of quantitative research on this subject is presumably related to its novelty and the high variability of Bitcoin markets. We are interested in investigating whether Bitcoin markets are attractive to noise traders. Specifically, we focus on feedback traders, a group of investors that has been found to create fertile ground for speculative bubbles (Sornette D. , 2017). While research on irrational behaviour and sentiment in cryptocurrency markets has received considerable attention, the influence of sentiment on feedback trading is yet to be determined. The central goal of this thesis is therefore to investigate the presence and dynamics of feedback trading, and how this is influenced by sentiment, in Bitcoin markets.

In this thesis we address the issue of sentiment and feedback trading in Bitcoin markets. The remainder of this thesis is structured as follows. In Section 2 we present the scope of our research, including an elaboration on the research questions we intend to answer. In Sections 3 – 6 we introduce the theoretical background relevant to the interpretation of the empirical results. The theoretical background on Bitcoin is introduced in Sections 3 and 4, with a broad overview on the history and emergence of Bitcoin as well as its underlying technology in Section 3. In Section 4 we further discuss the on-going debate on the classification of Bitcoin as an asset or as a currency. In addition, we take a closer look on the theoretical foundations on speculative bubbles in Sections 5 and 6. While Section 5 gives a comprehensive overview on the process of the formation and subsequent burst of speculative bubbles, Section 6 reviews relevant theory on sentiment and feedback trading. Thereafter, Sections 7 - 9 combine the two fields of research. In Section 7 we analyse Bitcoin markets with respect to theory on speculative bubbles, sentiment, and positive feedback. To empirically test the analysis conducted in Section 7, we introduce relevant methodology and quantitative models in Section 8. We present and make sense of the empirical results in Section 9, followed by a discussion with respect to theoretical and investment-related implications, as well as the limitations we deem relevant for future research in Section 10. To draw conclusion, Section 11 summarises the main results.

2. Research Scope

The aim of this section is to define the scope of our research and identify those areas of investor behaviour that we find particularly interesting. In the first two subsections, we introduce the research gap and present three concrete research questions. In the last subsection, we describe several a priori limitations that potentially bias our approach to research.

2.1 Research Gap

Since the introduction of Bitcoin, literature increasingly focuses on its potential and characteristics as a currency (Grinberg, 2011) (Badea & Rogojanu, 2012). With its presence in the media, also the interest in the characteristics and drivers of Bitcoin increased. For example, the discussion about whether Bitcoin can be considered an asset or a currency (Glaser, Zimmermann, Haferkorn, Weber, & Siering, 2014) and research about its characteristics as a potential asset (Katsiampa, 2017) received considerable attention. Research concerning the trading behaviour of the parties involved in the market, however, is limited. Trading strategies and its relationship with investor sentiment in Bitcoin markets have not yet been extensively tested. At the time of writing this thesis, only a few papers cover Bitcoin price formation from a combined behavioural and quantitative perspective and attempt to characterise traders' irrational behaviour. For example, Bouri(2018) measure herding in Bitcoin markets, while others apply text mining strategies to measure investor sentiment in cryptocurrency markets (see also Mai, Shan, Bai, Wang, & Chiang, 2018).

Sentiment and feedback trading have generally been studied in behavioural finance research as independent factors; nevertheless, we find limited studies on the link between these two, especially in cryptocurrency markets. The emerging nature of Bitcoin and the variability of its markets together with the ongoing debate about its (lack of) fundamental value (c.f. Section 5.3) has potentially discouraged further research on sentiment and feedback trading. The unique nature of this market that brings unknown price formation dynamics with soaring levels of volatility provides an interesting setting to further understand traders' actions from a more behavioural perspective, whose study so far has only scratched the surface.

2.2 Purpose and Research Questions

With this thesis we aim to investigate the relationship between investors' sentiment and feedback trading, and its direction and magnitude relative to the market volatility. We begin by reviewing relevant literature on speculative bubbles that gives us insights about the likely dynamics to be found when studying Bitcoin prices. Subsequently, we dig deeper into the subjects of sentiment and feedback trading and introduce the frameworks that will set the basis of our analysis. Establishing the theoretical background and communicating a thorough picture of Bitcoin markets sets the ground for the quantitative analysis of feedback trading in Bitcoin markets.

We attempt to contribute to literature on behavioural finance by quantitatively analysing a speculative market that is likely subject to irrational behaviour and trend chasing strategies. We seek to raise awareness amongst investors of the existing speculative forces to avoid periods of extreme irrational exuberance leading to market crashes. As we generally call upon well-established economic theories, we seek the expansion of knowledge about cryptocurrency markets in general, and Bitcoin in particular. With this thesis, we hope to shed light on sentiment and feedback trading in cryptocurrency markets and create more awareness amongst investors of the opportunities and pitfalls in such markets.

To advance the understanding of the matters above, the main research questions that we aim to answer are the following:

RQ1: *Which type of feedback trading dominates Bitcoin markets?*

RQ2: *What is the relationship between feedback trading and volatility?*

RQ3: *Does investor sentiment have an impact on feedback trading?*

2.3 Delimitation

We find several types of limitations when tackling the proposed research questions. First, as Bitcoin is a relatively new topic, we only find available price data starting from July 2010. This excludes past events of global financial crashes and bubbles that could have had effects on Bitcoin markets and added more information to our research worth to study.

Second, our choice to measure sentiment[1] and its subsequent influence on Bitcoin markets, although based on Baker and Wurgler's (2006) well-established approach, may seem controversial as we do not directly measure sentiment in Bitcoin markets but in the U.S. in general. The application of the Baker and Wurgler index to data reflecting sentiment in Bitcoin markets is not feasible for our thesis, as suitable proxies to sentiment, comparable to the ones Baker and Wurgler employ, have not been systematically investigated. We therefore decide to measure the level of sentiment in the U.S. markets and study its influence on Bitcoin markets. Moreover, the availability of data for calculating the sentiment proxies is limited to monthly records, confining the creation of the index to monthly (c.f. Section 8.3.3).

Lastly, the feedback trading models we utilise imply a conception of investors that bias the final conclusions. These models acknowledge the existence of rational traders as investors who take decisions upon fundamentals. This premise is, however, challenged by the nature of cryptocurrencies.

3. Background – Bitcoin and The Blockchain

Bitcoin is an electronic coin or token that was developed under the pseudonym Satoshi Nakamoto (2008) as a peer-to-peer electronic payment system that allows the transfer of cash from one party to another without the intervention of a financial institution. In other words, it is designed to operate under no central authority as all transactions and coin issuances are carried away collectively by the network itself (Nakamoto, 2008). Nakamoto defines an electronic coin as "a chain of digital signatures where each owner transfers the coin to the next by digitally signing a hash of the previous transaction and the public key of the next owner and adding these to the end of the chain".

The underlying technology that allows this process is called the Blockchain, a cryptographically secured ledger. A blockchain is a data set formed of different data packages, most commonly known as blocks, which each of them comprises a number of transactions. The Blockchain represents a complete ledger with all transactions and blocks history (Nofer, Gomber, & Hinz,

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[1] Throughout this thesis, we refer to investors' and traders' sentiment generally as sentiment.

Blockchain, 2017). Besides the transactions, each block contains a timestamp, the hash value of the previous block (unique value), and a nonce, which is a random number for verifying the hash, further ensuring its authenticity (Nofer, Gomber, & Hinz, Blockchain, 2017). In order to ensure the completion of the transactions, the system employs the so-called Bitcoin Miners who pack the transactions in a block that strictly fits the cryptographical rules, to later be accepted by the network (Bitcoin Project, 2019). This encrypted process also allows the user of the network to remain anonymous. The public will be able to see whether someone is sending money and the corresponding amount, but without personal information on specific users, ensuring anonymity (Nakamoto, 2008).

Other attempts to create digital money have occurred in the past (Dotdash, 2019) (Griffith, 2014), though one of the biggest advantages of Bitcoin and Blockchain that has determined its success is the prevention of the double-spending problem (i.e. the act of using the same electronic coin several times). On the other hand, one of the downsides of this technology is the scalability. Whereas Bitcoin supports around seven transaction per second, this number is over-shadowed by other payment platforms such as PayPal or VISA that are able to process up to nearly 200 and 1.500 transactions per second respectively (Altcoin Today, 2017) (CoinDesk, Inc., 2019). In spite of this, the number of transactions held by the Blockchain in Bitcoin keeps increasing (Figure 1) (BLOCKCHAIN LUXEMBOURG S.A., 2019).

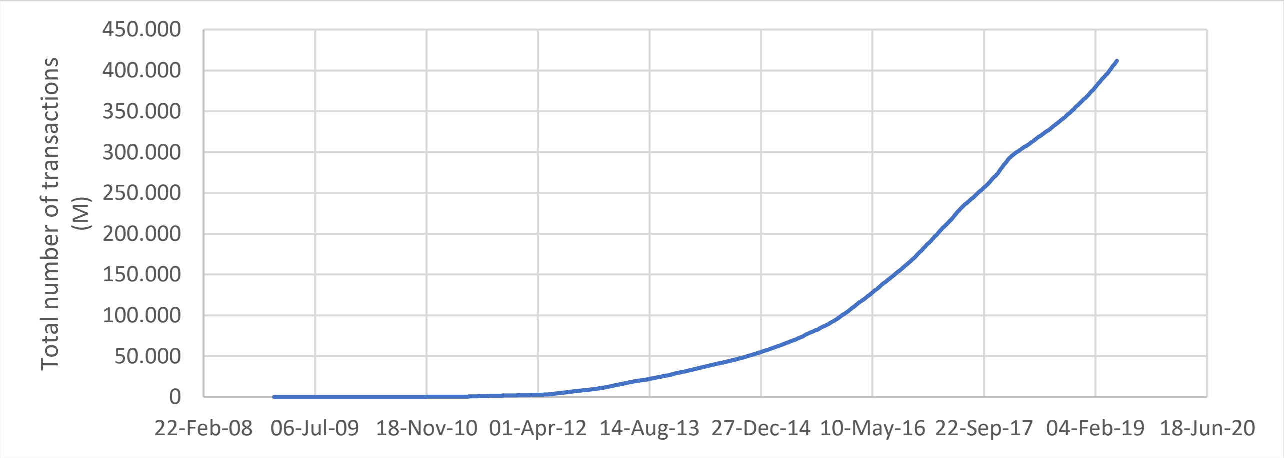

Figure 1 – Total number of transactions in Bitcoin

However, when analysing the total number of Bitcoin transactions, the question arises how many of these transactions are actually used to pay for goods or services? In fact, only a small fraction of the market capitalisation is utilised for this purpose (Petersen, 2018). Instead, most of investors employ Bitcoin as a speculative mean which, together with the lack of infrastructure surrounding it, may drive its potential as a payment method down (Glaser, Zimmermann, Haferkorn, Weber, & Siering, 2014).

The previously mentioned anonymity feature that involves the transaction process has also given way to a rising debate on Bitcoin regulation and government intervention. There are two main classes of criminal concerns that surround Bitcoin: money laundering issues and Bitcoin-facilitated crime (e.g. sale of illegal goods and services, or extortion) (Böhme, Christin, Edelman, & Moore, 2015).

Bitcoin, and therefore cryptocurrencies, originated in the aftermath of the 2007-2008 financial crisis. This crisis raised a debate about the current state of the global economy and unveiled trust issues towards the role of banks and financial institutions in general. Some authors have even addressed the creation of cryptocurrencies as a consequence of the financial crisis and a way to rebel against the current institutions and system (Halaburda, 2016a) (Weber, 2016).

As of 24th March 2019, Bitcoin is the largest cryptocurrency with a total market capitalisation of 70,540,000,000 USD (finance.yahoo.com, 2019). Its price is characterised by high volatility and has significantly increased since its releasing date, from an initial price of 0.008 USD to today´s value of above 4,000 USD (as of 24th of March, 2019) with an astonishing peak of nearly 20,000 USD in December 2017 (Higgins, Coindesk.com, 2017). Although Bitcoin was the first electronic coin to be developed and launched to market, many other developers have created new electronic coins and sold them to the market through the commonly known Initial Coin Offering (ICO). The ICO term was expanded in 2014 when Ethereum, currently the second largest cryptocurrency in terms of market capitalisation, was released to the market. In principle, this stream surged with the aim of creating an infrastructure that removes central authority and reduces the commissions charged on transactions, but throughout time it has also become a lucrative way to raise funds and look for the next big investment opportunity. Since the creation of Bitcoin in 2009, the total number of cryptocurrencies as of 24th of March 2019 has increased to 2,121 with a total market capitalisation of 140,174,543,664 USD (CoinMarketCap, 2019). Bitcoin, however, is still the most valued cryptocurrency with more than 50% of the total market capitalisation, followed by Ethereum with nearly 10% (CoinMarketCap, 2019).

Today, cryptocurrency markets share some characteristics typical for some of the most remembered bubbles in history, such as the tulip mania or the dotcom bubble in which speculation took over the market and price increases attracted more investors seeking large returns. Renowned economists and investors such as Robert Shiller or Warren Buffet have publicly announced their concern about the current stage of the cryptocurrency markets and even raise doubts about Bitcoin´s value with statements such as “Bitcoin has no unique value at all” (CNBC LLC, 2019) or “It looks like a bubble” (CNBC LLC, 2018).

Considering the aspects of cryptocurrency markets discussed in this section, Bitcoin and the Blockchain have been of particular interest to global economies for its potential to disrupt existing payment and monetary systems; the most interesting insights, however, may come from market design and users’ behaviour (Böhme, Christin, Edelman, & Moore, 2015). In a broad sense, two types of people who invest in cryptocurrencies are found: 1) those who believe in the value of its underlying technology as well as its potential as currency, 2) and those who use it exclusively as an asset due to its potential returns. We further discuss this dual use of cryptocurrencies in the next section.

4. How to Classify Cryptocurrencies?

Determining the status of cryptocurrencies as either alternative currencies or as a new class of (speculative) assets is a difficult endeavour and subject to an on-going debate. While the classification of cryptocurrencies may seem irrelevant at first, one must not belittle its economic implications. For instance, in portfolio management, currencies yield different strategic implications than assets. Also, currencies have been popular means to hedging while assets are prominent investment or speculation objects. The fact that governments cannot agree on a consistent approach to the classification of cryptocurrencies further stresses the complexity of the issue. The German authorities, for example, classify Bitcoin as a unit of account “for tax and trading purposes” (Van Alstyne, 2014), i.e. as a currency. The United States, on the contrary, consider Bitcoin as taxable property, i.e. as an asset. The following section sheds light on this ongoing debate by first illustrating supporting arguments for Bitcoin’s status as a currency and then arguing for the classification as an asset.

4.1 Bitcoin as a Currency

The creator of Bitcoin, Nakamoto, defines Bitcoin as a peer-to-peer electronic cash system designed for direct online payments between parties without the authorisation of a financial institution (Nakamoto, 2008). This definition implicates that the (original) intended usage was that of an alternative currency (c.f. Section 3). Furthermore, the process of mining cryptocurrencies was designed to imitate the mining costs of precious metals such as gold (Cheah & Fry, 2015). One stream of literature therefore compares cryptocurrencies to such precious metals that do not produce cash flows but might be traded for goods and services, thereby preserving their value. Bitcoin, for example, has characteristics in common with both commodity money (e.g. gold) and fiat money (e.g. U.S. dollar), thence often regarded as a hybrid between the two. Its scarcity by design is central to commodity money while its purpose as means of exchange is central to fiat money, i.e. a currency without intrinsic value (Baur, Hong, & Lee, 2018).

The European Central Bank (ECB) categorises cryptocurrencies as a subset of virtual currencies, defined as “unregulated, digital money which is issued and usually controlled by its developers, and used and accepted among the members of a specific virtual community” (European Central Bank, 2012), while acknowledging that this definition may call for updating in the future. The ECB classifies different cryptocurrency models based on its respective relation with real money and real economies, distinguishing three types: Closed currency schemes, currency schemes with unidirectional flow, and currencies with bidirectional flow.

Closed currency schemes comprise “in-game” currencies that have a neglectable relation to the real economy. For instance, players of World of Warcraft (WoW), an online role-play game by Blizzard Entertainment, can earn WoW Gold for accomplishments in the game. They can then trade that currency for advantages over other players in the game such as greater equipment. Buying and selling the WoW Gold outside of the game is strictly prohibited.

Cryptocurrencies with unidirectional flow, such as Facebook Credits, can be bought in the real world but not exchanged back. That is, Facebook Credits could be bought using standard means of payment (e.g. credit card) to buy virtual goods in Facebook games, but the credits could not be exchanged back to a real currency. In 2012, however, Facebook announced the cancellation of its own currency to “simplify the purchase experience” (British Broadcasting Corporation, 2012).

Cryptocurrencies with bidirectional flow can be bought and sold just as any other currency. This type of cryptocurrency has the greatest interaction with the real economy as it enables purchasing virtual as well as real goods. The Linden dollar for example, a cryptocurrency from the online game Second Life, could be purchased with regular currencies at exchange rates established by standard market mechanisms of supply and demand.

The ECB further distinguishes cryptocurrencies from electronic money. The monetary value of electronic money symbolises a claim on the issuing entity. This claim is characterised by three central criteria: It is stored electronically, it must be issued on a receipt stating a value that is no lower than the monetary value for which it was issued, and it must be generally accepted as a means of payment (European Central Bank, 2012).

While cryptocurrencies are increasingly being accepted as a means of exchange (SatoshiLabs s.r.o., 2019), there is one major difference to electronic money: The ties between electronic and physical money lie in a legal foundation and are bound to the same format while the unit of account of cryptocurrencies is purely virtual. A unit of account, however, is an essential criterion of any currency (Dwyer, 2015). The above definitions emphasise the exchange-nature of money by classifying cryptocurrencies as a mean to exchanging goods. Furthermore, Frisby (2014) emphasises that the core features of Bitcoin, most notably its convertibility, low transaction costs, and convenience, are also features of standard currencies. Another criterion is the store of value (Cheah & Fry, 2015). Van Alstyne (2014), for example, argues that Bitcoin ought to be supported by state authorities with tax and spending powers to have value. With respect to the claim theory of money, Bitcoin serves as a claim on the issuer, it represents a social relation. Furthermore, a number of researchers acknowledge Bitcoin as a legal tender considering tax liabilities and juridical debt (Bell, 2001) (Dequech, 2013) (Ingham, 2013). The (fundamental) value of cryptocurrencies, however, cannot be quantified and agreed upon with satisfactory consensus (c.f. Section 5.3).

4.2 Bitcoin as an Asset

Despite the original use as an alternative currency, another branch of research suggests that cryptocurrencies also exhibit characteristics of (speculative) assets. Indeed, Cheah and Fry (2015) observe that Bitcoin exhibits unpredictable levels of volatility that “potentially undermine[s] the role Bitcoin plays as a unit of account”. Such levels of volatility imply that traders of Bitcoin cover a spread over the Bitcoin price in its original currency if the prices change. Baur et al. (2018) further note that the demand for an asset could contribute to its volatility. Furthermore, 70% of Bitcoins are held in dormant accounts (Weber, 2016), suggesting that Bitcoin functions more as an asset than as a currency. Indeed, the main intention of investors seems to be to employ Bitcoin as an object of speculation instead of as a mean of payment. A substantial growth in cryptocurrency prices further suggests that one could regard them as a new class of investment assets (Corbet, Meegan, Larkin, Lucey, & Yarovaya, 2018).

Baur et al. (2018) examined the financial characteristics of Bitcoin to determine whether it should be characterised as an asset or as a currency. By first comparing Bitcoin to different financial assets and then analysing the intentions of Bitcoin traders, Baur et al. (2018) find that a third of

Bitcoins are owned by investors that only hold and not trade it, but only a minority of Bitcoins is used as currency. They therefore conclude that Bitcoin is primarily used for investment purposes. This conclusion is supported and extended to other cryptocurrencies in the research community (see for example Bariviera, Basgall, Hasperué, & Naiouf, 2017; Baur, Dimpfl, & Kuck, 2018; Baur, Hong, & Lee, 2018; Glaser, Zimmermann, Haferkorn, Weber, & Siering, 2014). We therefore consider Bitcoin as an asset in the proceedings of this thesis.

5. Bubble Mechanics

The price of Bitcoin grew within 12 months from a value of 1,000 USD in January 2017 to a maximum of nearly 20,000 USD in December 2017 (CoinDesk, Inc., 2019), accompanied by constant doubts about its functionality and fundamental value, giving credit to academics to believe that Bitcoin is a bubble. The idea that Bitcoin prices resemble past events of highly overpriced assets, encourages us to further understand how these events occur and to identify the antecedents that precipitate prices to experience both large initial deviations and a subsequent rough correction.

In the aftermath of the financial crisis 2008, research on the speculative dynamics of financial bubbles has received considerable attention (Sornette D. , 2017). In this section, we introduce basic theory and the main concepts describing the mechanics characterising financial bubbles. According to Roubini and Mihm (2010), Kindleberger's '*Manias, Panics and Crashes*' (1978) was one of the first attempts to provide a comprehensive, general theory of financial crises. Kindleberger advanced the understanding of financial bubbles and crises on which we elaborate in the following section.

5.1. The Emergence of Financial Bubbles

Financial bubbles evolve slowly in the beginning but, over time, acceleratingly exhibit instability nourished by behavioural dynamics such as sentiment and positive feedback (cf. Section 6). Now, consider a given market that is performing well. Ideally, prices reflect the market participants' beliefs of the fundamental values of assets. The market starts to attract an increasing number of investors, raising expectations of easy profits until the asset prices no longer follow beliefs of fundamental values but instead reflect the expectations of future returns. Indeed, the seed of a financial bubble is a profit opportunity, prompted by an endogenous factor, resulting in a price increase (Kaizoji & Sornette, 2010) (Montier, 2009). Next, more sophisticated investors exploit that opportunity, further stimulating appreciation (Sornette & Cauwels, 2015). Extrapolated high returns then might spark euphoria, attract irrational, or noise, investors, resulting in a spiral of demand and rising prices (Sornette & Cauwels, 2015). Collective emergent behaviour and feedback mechanisms are key amplifiers of these bubble mechanics on which we shed light in Section 6.

The price and demand spiral is further intensified by monetary policy and bank credit creation, facilitating an imbalance between supply and demand with much higher demand than supply (Montier, 2009) (Kaizoji & Sornette, 2010). During periods of euphoria, seamless access to loans makes it easy for investors to borrow funds, which are likely to be invested into illiquid assets such as stocks and real estate (Janeway, 2012). As a result, speculation in equity markets is fuelled by speculation in credit markets. In periods of increasing economic activity, such as the one we investigate later, investors are likely to be optimistic about returns; combined with less risk-averse credit suppliers, such optimism increases the risk of a financial bubble (Kindleberger, 1978). It is now likely that the market structure changes abruptly, entering a new system characterised no longer by rational approaches but by sentiment and simple heuristics (Sornette & Cauwels, 2015). A market driven by sentiment faces an increased risk of instability. According to Sornette (2017), such (systemic) instability is rooted in unsustainable and disproportionate growth of price driven by over-optimism and positive feedback loops.

The last stage of a financial bubble is called financial distress. If the market is destabilised by the mechanisms exposed above, unrestrained positive feedback trading can result in abnormal returns and, in turn, in serious deviations from the theoretical fundamental value (cf. Section 5.3). Instable markets are more vulnerable to exogenous shocks than stable ones, increasing the risk of severe financial distress (Sornette D. , 2017). In periods of financial distress, profits cease to rise, and investors might cash out (Montier, 2009). Once the general need for liquidity is no longer satisfied, exogenous events, such as governmental regulations on taxes or interest rates, might prompt the bubble to burst (Kindleberger, 1978). Indeed, while exogenous factors may give rise to the bubble to burst, the behavioural dynamics amongst investors endogenously set the seed for the financial bubble to develop.

Following Sornette (2017) and Kindleberger (1978), we suspect that a central antecedent of financial bubbles is unsustainable growth of prices initiated by irrational behaviour resulting in the deviation of an asset’s price from fundamental value beliefs. For the scope of this thesis, we therefore define the term “bubble” as the deviation of an asset’s price from its fundamental value.

5.2 Speculative Bubbles: Rational and Irrational

Shiller (2015) denotes that speculative bubbles, a special subcategory of asset bubbles, exhibit levels of social epidemic behaviour, or fad, following principles of social psychology, flawed media, and information channels. The demand of investors during speculative bubbles is exclusively driven by the expectation of a future sale for a larger value. Speculative bubbles can either be rational or irrational, depending on the investor's intentions (Dale, Johnson, & Tang, 2005).

Rational bubbles occur when investors rationally participate in speculative markets because they expect to benefit from the rising price levels. This expectation results in a deviation of prices from fundamentals. Johansen et al. (2000), for example, reason that it is rational for investors to continue participating in the market as a crash is not a deterministic consequence of a speculative bubble. In other words, as long as there is a finite probability that the bubble ends without a crash, rational speculators buy an overpriced asset expecting to sell it at an even higher price, being compensated for taking the risk by a higher rate of growth. That is, in this kind of bubble, rational speculators are fully aware of the 'bubble state' of the market but expect to benefit from the bubble by selling an overpriced good to someone else willing to pay that price.

Irrational bubbles on the other hand are driven by emotional investor behaviour. This kind of behaviour ignores fundamental values, thereby breaking the relationship between fundamental value and price (Dale, Johnson, & Tang, 2005). Instead, investors consult simple heuristics that adhere to market sentiments, form over-optimistic expectations, or follow fads and fashions (Dwyer, 2015) (Shiller R. J., 2015) (Weber, 2016). Investors following such heuristics are often referred to as noise investors. Black (1986) describes noise trading as trading on noise, the contrast of information, "as if it was information". Such noise traders participate in the market based on noise, independent from market movements, believing that the noise is valuable information. By definition, such traders are insensitive to present prices (Sornette D. , 2017).

Roots of speculative bubbles include, but are not limited to, self-fulfilling expectations, endowment of irrelevant exogenous variables with asset pricing value, and the mispricing of fundamentals (Cheah & Fry, 2015). In the following subsection we elaborate on the mispricing of fundamentals by elaborating on two contrasting theories on the fundamental value of Bitcoin.

5.3. Speculative Bubbles in Cryptocurrency Markets and the Fundamental Value of Bitcoin

As we have seen in Section 5.1, the deviation of an asset's price from the fundamental value beliefs is central to the definition of a financial bubble as well as a key determinant for a speculative setting (c.f. section 6.2.1.). Furthermore, considering the role of derivatives as an antecedent and magnifier to financial bubbles (Sornette D. , 2017), the introduction of cryptocurrency derivatives to mainstream markets (British Broadcasting Corporation, 2017) emphasises the need to understand the drivers of cryptocurrency prices. While it is already difficult to value standard assets, there is no consensus in research on how to quantify the fundamental value of cryptocurrencies as valuing them is new territory in economics. Though frequently compared to notorious past speculative manias, such as the tulip mania, cryptocurrencies differ from these due to its dual purpose as an asset *and* a currency (cf. Section 4). It is therefore important to note that the categorisation of Bitcoin as an asset (c.f. Section 4.2) is imperative to the discussion of its fundamental value as both approaches presented in this section were originally designed to determine the fundamental value of assets. In general, we identify two main competing approaches to the fundamental value of cryptocurrencies: The Cost of Production Model or defining the fundamental value as zero.

The Cost of Production Model ties the value of an asset to the cost of its production. Jenssen (2014), for example, claims that the fact that mining cryptocurrencies is costly in terms of resources is indicative of its value. Garcia et al. (2014) hypothesise that the cost of mining one unit of currency matters for determining its fundamental value as it serves as a lower bound. Hayes (2017, 2019) also argues that cryptocurrencies do have an intrinsic value and identifies three main drivers of the value of cryptocurrencies: the degree of competition amongst the cryptocurrency miners, the speed of mining, and the complexity of the algorithms employed for mining.

He first determines the correlations between the cryptocurrency value and the amount of computational power needed to mine a coin, the rate of coins mined per minute, the ratio of already mined coins to the theoretical maximum to be mined, the complexity of the algorithm used for mining, and the longevity of the cryptocurrency. He finds that more than 84% of the proportionate value creation can be explained by the computational power needed to mine a coin, the rate of coins mined per minute, and the complexity of the algorithm used for mining. Hayes concludes that the "relative cost of production on the margin drive value formation for cryptocurrencies". The primary cost factor in mining cryptocurrencies is the energy consumption which has been constantly increasing (Hayes, 2019). Other costs include access to internet and hardware (maintenance).

Hayes (2017) models the decision to attempt mining Bitcoin by utilising the price of electricity, the energy consumption per unit mined, the dollar price of bitcoin, and the estimated number of Bitcoins mined per day as inputs. He expresses the expected number of Bitcoins mined per day as

$$\frac{BTC^*}{day} = \left(\frac{\blacklozenge \rho * sec_{\mathrm{hr}}}{\blacksquare * 2^{32}} \right) hr_{day} \tag{1}$$

with BTC/day* as the expected daily amount of Bitcoin when mining directly, $\blacklozenge$ the reward for creating blocks (expressed in BTC), $\blacksquare$ the mining difficulty, sec_{hr} the number of seconds in an hour, hr_{day} the number of hours in a day, and ρ the hashing power, i.e. the power a computer or hardware uses to run and solve hashing algorithms. Such algorithms are employed for generating new cryptocurrencies and allowing transactions between them. Hayes further expresses the cost of mining per day, E_{day}, as:

$$E_{day} = \left(\frac{\rho}{1000} \right) \left(\frac{\$}{kWh} * \frac{WperGH}{s} * hr_{day} \right) \tag{2}$$

Recalling basic microeconomic theory, Hayes hypothesises about Bitcoin’s fundamental value that it should be equal to the marginal product of mining, which in turn should theoretically be equal to the marginal cost in a competitive market (e.g. Case & Fair, 2006). As the cost of mining is expressed in $/day and the expected number of Bitcoins mined per day in BTC/day, the ratio of the cost of mining per day and the expected number of Bitcoins per day results in the $/BTC price level:

$$P^* = \frac{E_{day}}{BTC/day^*} \tag{3}$$

Hayes defines the above equation as the lower bound for the market price, or the fair value of one unit of Bitcoin. He notes, however, that both the model and results must be taken with a grain of salt as substantial volatility and market price fluctuations present in cryptocurrency markets could imply that determining a fundamental value is meaningless in practice.

The second main approach to valuation holds that cryptocurrencies have no fundamental value. Hanley (2013), for example, argues that Bitcoin prices are merely a market valuation without a fundamental value supporting it. Cheah and Fry (2015) further note that the fluctuations in Bitcoin prices are not indicative of a consistent fundamental value.

Following Johansen et al. (2000), Cheah and Fry (2015) empirically investigate whether Bitcoin exhibits characteristics of speculative bubbles, concluding that Bitcoin indeed shows signs of a speculative bubble. As part of this investigation, they further employ the estimate of an asset's fundamental price in a non-bubble regime, as proposed by Fry (2014b):

$$P_F(t) := E\big(P(t)\big) = P(0)e^{\bar{\mu}t} \tag{4}$$

where P_t denotes the price of an asset at time t, μ the intrinsic constant rate of return, and $\bar{\mu} = \mu + \sigma^2/2$, with σ^2 as the intrinsic constant level of risk. It is important to note that the model implies that financial time series, in the long-run, frequently feature approximately exponential behaviour (Campbell, Lo, & MacKinlay, 1997). Defining this model of an asset's fundamental value permits the calculation of the average difference between this fundamental price and prices in potential bubbles, thereby facilitating the detection of a bubble regime. Cheah and Fry (2015) find significant evidence that Bitcoin exhibits bubble characteristics in 2013. They further find that $\bar{\mu}$ is not statistically different from zero, concluding that the increases in price are severe enough that the estimated underlying fundamental price is equal to zero. This view is further supported by both Jamie Dimon (Son, Levitt, & Louis, 2017), the CEO of JP Morgan Chase, and the Wall Street Journal (Mackintosh, 2017), stating that the fundamental value of Bitcoin is zero.

6. Sentiment and Positive Feedback

Throughout the history of financial markets, numerous events of dramatic changes in stock prices occurred that defy human explanation. Classic economic theory, presupposing rational expectations dominate the market, does not yet offer a logical explanation to these events. Therefore, researchers in behavioural finance have been searching for alternatives outside of the boundaries of rational financial behaviour that may explain such events.

In this section we first elaborate on the well-established framework proposed by De Long et al. (1990) that provides an integral part of the theoretical setting and relevant assumptions of this thesis. In this framework, rational investors share the market with irrational investors, which contemplates price deviations from fundamentals. Thereafter we take a closer look on sentiment and positive feedback as the main factors that influence price deviations from fundamental values, thereby setting the basis of our empirical analysis in Section 8.

6.1. Rational and Irrational Traders

In accordance with the work by Black (1986) and De Long et al. (1990), rational traders (also referred to as arbitrageurs) coexist with irrational or noise traders (also referred to as feedback traders), who follow simple heuristics that tend to affect prices and returns in an unpredictable way.

The existence of irrational traders has been widely recognized in the literature. Economists and asset price formation theorists, however, have left them out of most discussions on asset price formation (Delong et al., 1990). Friedman (1953) and Fama (1965) were amongst the first to discuss the lack of influence of noise traders on prices by addressing the importance of the arbitrage exerted by rational traders, who bet against noise traders and bring prices back to fundamentals. Their frameworks, nevertheless, contemplated complete markets in which there are no limits to arbitrage. DeLong et al. (1990) examined such arguments by focusing strictly on the limits to arbitrage investor misperceptions. Under the assumption that rational investors are risk averse and have short horizons, their motivation and propensity to bet against irrational traders might be limited (De Long, Shleifer, Summers, & Waldmann, 1990).

On one hand, arbitrage is limited by fundamental risk. Price deviations from fundamental values might take a long time to correct; during this time, rational traders betting against noise traders are subject to a high degree of fundamental risk that limits arbitrage even when the horizon is infinite due to investor risk aversion (Shiller R. J., 1984) (Figlewski, 1979). On the other hand, an important source of risk affecting short-horizon rational investors is the fact that the "beliefs" of noise investors, and thus their demand, might remain constant for a long period of time. Consequently, prices might continue to deviate from fundamental values in the process (De Long, Shleifer, Summers, & Waldmann, 1990). For instance, a rational trader who is short-selling an asset that has been driven up by noise traders, must consider the possibility of the asset moving further up in the short-run. If investors are optimistic about the price of the asset, further increases are likely. In turn, if the arbitrageur needs to liquidate before the price corrects, they will suffer a loss. The fear of this scenario possibly discourages arbitrageurs from taking such positions (De Long, Shleifer, Summers, & Waldmann, 1990). Furthermore, recalling theory on rational speculative bubbles (c.f. Section 5.2), it might be rational for investors in certain situations to participate in the bubble instead of betting against noise traders as prices might keep rising. To this end, it is essential to differentiate between rational speculation and rational trading. While we refer to rationality in financial markets as trading on fundamentals, rational speculation falls within the domain of noise trading. That is, rational speculators, or negative feedback traders, base their strategies on historical returns and not on fundamentals (c.f. Section 6.1.).

The conclusions reached above essentially come from the observation that arbitrage is not sufficient to eliminate noise, since noise brings risk to the market. Noise traders happen to falsely believe that they possess valuable and correct information (‘noise’) about the future prospect of a risky asset; since these beliefs are usually inaccurate, they become unpredictable (De Long, Shleifer, Summers, & Waldmann, 1990). These traders will therefore select their portfolio based on their erroneous beliefs. In response to irrational trader decisions, more sophisticated traders might try to take advantage of them and exploit their market misperceptions, thus buying when irrational traders depress prices and selling when noise traders push prices up (De Long, Shleifer, Summers, & Waldmann, 1990). For example, assume that the price of a stock in a given market is below the theoretical fundamental value. In this scenario, rational investors are likely to seize the opportunity and buy that stock. This purchase possibly drives the stock price marginally up. Irrational traders are then likely to react to the resulting positive return and further the positive trend by purchasing the stock for an even higher price. This exemplifies a general representation of noise trader strategies: buy winners and sell losers.

Eventually, arbitrageurs will find betting against this type of investor risky and too costly. Therefore, the deviation of prices from fundamentals must be taken into account when investing in and theorising about financial markets. The theoretical context above serves as a framework for the remainder of this thesis. This framework yields two important assumptions: first, we assume that investors are subject to sentiment (also addressed as beliefs or opinions), and second, we assume that arbitrage is limited since betting against noise traders is costly and risky.

6.2. Sentiment in Financial Markets

Sentiment in financial markets can be defined as “fluctuations in risk tolerance or [to] overly optimistic or pessimistic cash flow forecasts that will have an impact on asset prices different from the impact of fundamentals” (Chau, Deesomsak, & Lau, 2011) (Edelen, Marcus, & Tehranian, 2010). This definition is aligned with Baker and Wurgler (2006, 2007), whose research is a central element of this thesis. They define sentiment as a belief about future cash flows and investment risks that is not justified by the information at hand. All things considered, most approaches to investor sentiment come from cognitive psychology analysing the influence of behavioural biases on investor decision making (Kahneman & Riepe, 1998).

Sentiment can be systematised by two basic states; pessimism (negative or low sentiment) and optimism (positive or high sentiment) that represent attitudes taken part by irrational investors, assuming that optimism will lead to price rises and vice versa (Baker & Wurgler, 2007). For simplicity, neutral sentiment will be recognised as no sentiment and will have no further effect on prices. Following this definition, one of the challenges has been to identify and explain this formation of beliefs that might lead to a deviation of prices from fundamental values (Barberis, Shleifer, & Vishny, 1998).

Another definition of sentiment that is proposed by Baker and Wurgler (2006) considers sentiment as "the propensity to speculate". Following this definition, sentiment is a central determinant of the demand for speculative assets. This definition further implies that not all assets are equally speculative; those assets more exposed to sentiment are more likely to be speculative than assets with less exposure. The next section further elaborates on assets that are more prone to sentiment exposure.

6.2.1. Theoretical Effects of Sentiment on Prices

Following the framework proposed by DeLong et al. (1990), we assume that two types of investors compete in the market, rational arbitrageurs who are not directly affected by sentiment, and irrational traders who are subject to exogenous factors. Moreover, we assume that rational investors are limited in several ways such as risk and costs derived from short selling, that possibly results in deviations of stock prices from fundamental values. In behavioural finance theory, mispricing of stocks is a consequence of a change in sentiment of irrational traders combined with trading limitations (Baker & Wurgler, 2007).

The main conjecture extracted from this framework is that not all securities are equally sensitive to sentiment given the same level of difficulty to arbitrage; those that are more subject to sentiment exhibit a tendency to be more speculative (Baker & Wurgler, 2007). This raises the question of which stocks tend to be more speculative? Baker and Wurgler (2006, 2007) state that the difficulty and subjectivity in estimating the intrinsic value of stocks is the key characteristic that determines the tendency to speculation. In this regard, young stocks with limited information and insufficient tracks of profit and loss are likely to be subject to sentiment changes due to their uncertain future with high potential to experience profits and growth. Moreover, research shows that those small, young, unprofitable, and exhibiting a large growth stocks are generally costlier to arbitrage (D'Avolio, 2002), which gives way to speculation. To this end, we understand that those securities that are difficult to value tend to be more speculative and subject to sentiment. Considering the uncertainty regarding intrinsic value and basic buy-and-sell trading options (for most of its lifetime), Bitcoin could be considered a speculative asset.

The theoretical effects of sentiment on stock prices are exemplified by Figure 2 (Baker & Wurgler, 2007), where the valuation level is plotted conditional to the degree of speculation when sentiment is high, low or overall.

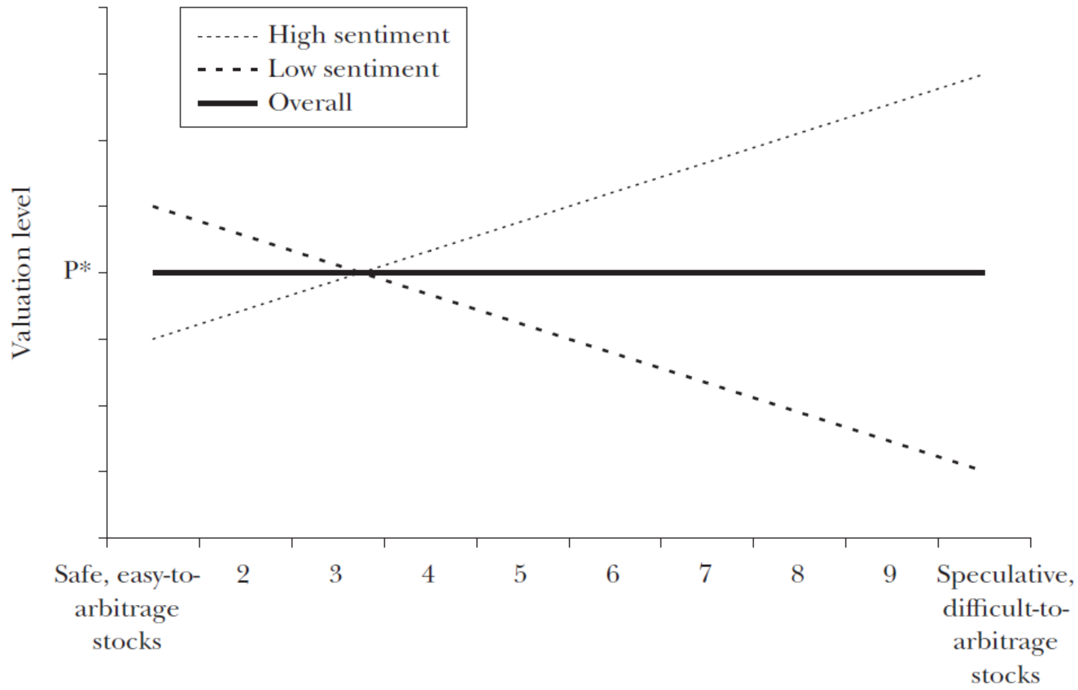

Figure 2 - Theoretical Effects of Investor Sentiment on Different Types of Stocks

Note that high sentiment (optimism) is associated with strong overpricing for those speculative stocks that are hard to arbitrage, whereas low sentiment (pessimism) works in the other direction. When sentiment does not play a role, valuation levels are assumed to be correct (P*).

6.2.2. Approaches to Sentiment

Previous literature on sentiment (see, for example, De Long, Shleifer, Summers, & Waldmann, 1990; Shleifer & Vichny, 1997) states that investor sentiment can profoundly influence prices and result in the deviation from fundamentals if certain conditions, that resemble real markets, are met. For example, if short-selling is too risky for rational investors, sentiment-driven irrational investors are likely to exert a larger impact on prices. This discovery encouraged academics to further study the influence of sentiment and use several proxies and measurements of sentiment that we cover in this subsection. The behavioural finance literature has mainly focused on the cross-sectional and the time-series relationship between sentiment and market returns (Chau, Deesomsak, & Lau, 2011), how sentiment affects corporate decisions (Lamont & Stein, 2005), and its predictive power on stock returns. It is worth mentioning that the models presented in this subsection are to some extent controversial and difficult to test, since they usually involve sources of sentiment that are, in any case, difficult to measure.

Daniel et al. (1998) and Barberis et al. (1998) developed the first well-researched sentiment models that attempt to explain how the behavioural biases of investors affect prices based on trader over-reaction and under-reaction to news as a source of sentiment. As these models are difficult to test empirically, subsequent literature moved to more practical market performance-based approaches.

Baker and Wurgler (2007) offer an exhaustive overview of sentiment measures which can be divided into direct and indirect sentiment measures that have been widely employed and are well-established in research. Direct measures are obtained by asking investors about how they feel about the market through surveys. Robert Shiller has been carrying out such surveys since 1989 with a simple, direct question: "What do you think is the probability of a catastrophic stock market crash in the U.S., like that of October 28, 1929, or October 19, 1987, in the next six months?", where he finds that generally investors tend to overestimate the probabilities of a crash. Other widely recognised survey-based sentiment indices are the University of Michigan Consumer Sentiment Index, The UBS/Gallup Index, or the Conference Board Consumer Confidence Index. Brown and Cliff (2005) utilised the above-mentioned direct survey measures to relate sentiment to stock price fluctuations from fundamental values. They test two hypotheses: Firstly, high optimism leads to market overvaluation, and secondly, high current level of sentiment lead to low long-term cumulative returns as the market always reverts to fundamentals. These hypotheses are tested by directly relating the level of sentiment to market mispricing as indexed by the Dow Jones Industrial Average pricing errors retrieved from Bakshi and Chen (2005). Brown and Cliff (2005) found robust evidence on price movements predictability from direct surveys.

Surveys, however, have often raised concerns about the veracity of investors' answers that might not fully reflect reality, even if the questions have been answered honestly (Shiller R. J., 2015). To put it differently, investors may act in a different way than declared in their answer. Moreover, Da et al. (2015) addressed some limitations of survey based predictive models such as data shortages (as surveys are generally conducted weekly or monthly) and raise doubts about the incentives to answer the enquiries truthfully and carefully. Intuitively, a conflict of interest might be found when responding to certain questions as respondents are also participants in markets and might be willing to influence it in certain way. In other words, investors might attempt to manipulate the market by giving false statements, or they might be reluctant to share potentially valuable information.

The reasons given above to not trust direct sentiment measures have bestowed more credit to indirect measures. Indirect measures are financial market-based indicators that relate mainly to market performance (Baker & Wurgler, 2006). Gervais et al. (2001) unveil trading volumes as a good proxy of investors' sentiment and find that high (low) trading volumes leads to higher (lower) returns. Baker and Stein (2004), identify trading volume as a sign of market liquidity and add that when short-selling is costlier than opening and closing positions, irrational traders will find more incentives to trade and bet for those stocks with a recent past of positive returns, further increasing its price. Scheinkman and Xiong (2003) address events in the past such as the internet (Dotcom) bubble where high prices and trading volumes coexisted, and further prove how under short-selling constraints, asset owners will have the option to sell to agents with more optimistic beliefs, thus acknowledging the relevancy of sentiment to prices. Another widely recognised indirect proxy to investors' sentiment is the level of close-end fund discounts. A number of researchers, such as Lee, Shleifer and Thaler (1991), Neal and Wheatley (1998), or Zweig (1973), state that, even though close-end funds do not represent a relevant part of the assets traded, the changing sentiment of investors towards them explains fluctuations in their price formation. Complementarily, Baker and Wurgler (2004a) (2004b) found that the dividend premium for dividend paying stocks is inversely related to sentiment. This may come from the sensation of "safety" the dividends convey to investors (c.f. Section 8.2.1).

Finally, other indirect proxies to sentiment found in literature are mutual fund flows, IPO volume (covered in Section 8.2.1), or insider trading (Baker & Wurgler, 2007). To this day, however, the probably most publicly recognised indirect investor sentiment indicator is the CBOE volatility index (VIX) developed by R.E. Whaley (1993), also known as the Fear Index, or Fear Gauge. The index utilises options to calculate the short-term volatility of the S&P 500. It is therefore a measure of the volatility as implied by options, a concept derived from the Black-Scholes model (1973), indicating the intention of investors towards hedging. In this regard, when investors increase their hedging activities, identified by the VIX as an increase of the price of PUT options, it is assumed that the market is expecting an upcoming bearish trend (Whaley, 2000). That is, a low VIX suggests that investors are generally optimistic while a high VIX is indicative of uncertainty.

A large body of literature employs these proxies to sentiment or constructs composite indices that are able to capture these altogether (Baker & Wurgler, 2006) (Brown & Cliff, 2004). In this regard, Baker and Wurgler's (2006, 2007) sentiment index represents one of the most accepted approaches to measure sentiment in literature. They developed a top-down approach to sentiment that increased the awareness of the influence of sentiment in stock prices by utilising six different market-based proxies and creating an index following a principal component analysis method. In Section 8.2. we explain the methodology of the data collection and index construction process in detail as it is a core element of the empirical analysis conducted in Section 9.

Another interesting approach to estimate investor sentiment has emerged only recently: The usage of text mining and sentiment analysis algorithms to retrieve information regarding investors' mood, further enhanced by the massive amount of data available from social media platforms and blogs. In fact, recent studies demonstrated that sentiment analysis executed using social media data can predict the market to some extent (Nofer & Hinz, 2015) (Sul, Dennis, & Yuan, 2017). For example, Colianni et al. (2015) successfully predicted Bitcoin price changes from the sentiment of tweets, yet, these studies are still exposed to numerous limitations. For example, the assignment of accurate sentiment labels to short texts remains a difficult endeavour as choices, such as preferred dictionary and the categorisation approach into positive and neutral sentiment, influence the resulting predictive power considerably.

6.2.3. Sentiment and Bitcoin

The literature in the field of behavioural finance investigating the effects of sentiment on Bitcoin remains relatively scarce; nevertheless, the interest is clearly increasing as cryptocurrency markets exhibit characteristics of exuberance. Recently, Baig et al. (2019) have found strong evidence of price clustering when the level of sentiment amongst participants is high as a consequence of uncertainty. Furthermore, Mai et al. (2018) investigate the effects of social media on Bitcoin prices with the following interesting conclusion: Social media´s most influencing effects on Bitcoin prices are mainly driven by the silent majority, i.e. "the 95 percent of users who are less active and whose contributions amount to less than 40 percent of total messages".

In spite of the shortage of literature on this topic, several organizations have tried to establish indices that can measure the level of sentiment in different cryptocurrency markets. One of them it is called "Fear & Greed index" which displays an interesting combination of the direct and indirect proxies highlighted above from volatility and trading volume, to surveys, social media text mining and Google Trends (Turner Broadcasting System, Inc., 2019). In contrast, the CCSIX Beta (2019) offers an exclusive text mining sentiment analysis of the social media content of the top six cryptocurrencies where the overall sentiment level is calculated as the average value of the six cryptos relative to social media content, weighted by market cap. Although the relevance and influence of these indices have not been established yet, they could be considered as a future area of research. As these indices are not yet recognised by relevant literature, however, we proceed with the Baker and Wurgler sentiment index instead.

In summary, behavioural finance researchers agree that noise traders are likely to take decisions based on simple heuristics such as sentiment (Barber & Odean, 2013) (Baker & Wurgler, 2007). Bitcoin represents a new phenomenon in society that is not yet completely understood due to its level of complexity. Factors such as the limited research and information sources, the lack of understanding of its price formation, as well as the technical knowledge required to understand the cryptography and algorithms involved in the system, increase the level of susceptibility of investors towards sentiment as it can potentially play a relevant role in the volatility of Bitcoin prices.

6.3. Feedback Trading

We understand positive feedback in financial markets following Robert Shiller's (2015) definition: It is the process in which initial stock price increases lead to further price increases, as the effects of the initial rise in prices feed back into higher prices driven by investors' increased demand. Investors following positive feedback strategies base their decisions on historical data (Dai & Yang, 2018) but not on expectations on future value. Theory on positive feedback is widespread. There is, however, no consistency in terminology amongst authors as positive feedback trading is not always referred to under the same name. Other expressions to address positive feedback trading include vicious circles, bandwagon effect, or speculative bubble (Shiller R. J., 2015). Numerous studies have examined the role of feedback trading in stock prices and acknowledge the existence of feedback traders (Long, Shleifer, Summers, & Waldmann, 1990), previously referred to as noise or irrational traders in this thesis.

Different types of feedback mechanisms are observed in the market (Shiller R. J., 2015). Shiller (2015) points out three that can potentially influence prices:

1) Price-to-price is the most recurrent and basic mechanism. Price increases, as a consequence of investor enthusiasm or sentiment, lead to further price increases.

2) Price-to-GDP-to-price, normally observed in the housing market, is the increase in the value of stocks and houses resulting in greater wealth and optimism. It feeds back and translates into an increase of consumption and investment in objects such as more houses (as investors tend to assume that they will always be able to find someone willing to pay a higher price), further increasing price levels.

3) Price-to-corporate to earnings-to-price is understood as the consequence of an increase in consumption driven by an increase in stock prices, that boosts company fundamentals, again resulting in further increases in prices.

6.3.1. Feedback Traders

Positive feedback investors will generally buy securities when prices are rising and sell when prices are decreasing (c.f. Section 6.1.). De Long et al. (1990) found that in the presence of rational traders, feedback trading can be destabilising as arbitrage will not be able to balance the market to compensate. When rational traders receive positive news about the market affecting the fundamental value of stocks and decide to trade on that news (buy stock), they realize the potential effect of their actions on feedback traders. Consequently, rational traders anticipating further purchases from irrational traders or trend-chasers tomorrow, may decide to buy more today which ultimately results in augmented deviation of prices from fundamentals. Hence, these originally rational traders would be acting as rational speculators (c.f. Setion 5.2.) that take advantage of feedback trading (Long, Shleifer, Summers, & Waldmann, 1990).

Next to positive feedback trading, we also contemplate negative feedback trading. Negative feedback traders are characterised by buying when prices drop and selling after a rise, a strategy opposite to positive feedback trading (Goetzmann & Massa, 2002). Negative feedback trading, even though it might be considered rational (speculation) as it attempts to take advantage of positive feedback traders, is a behavioural pattern that is not based on any fundamental approach to prices. This strategy is also recognized as contrarian investing and can help to lower volatility on markets (Drehmann, Oechssler, & Roider, 2005).

6.3.2. Previous Research on Autocorrelation in Stock Returns

De Long et al. (1990) and Shiller et al. (1984) introduced frameworks that consider heterogenous investors and consequently acknowledge feedback traders. Cutler et al. extended on this approach by studying the autocorrelation properties of stock returns and further proving the existence of feedback mechanism in the market by finding patterns of serial correlation in stock returns (Cutler, Poterba, & Summers, 1990).

In general, the two most widely accepted reasons for autocorrelations of stock returns are the biases caused by non-synchronous trading (Lo & Craig Mackinlay, 1990), and the time-varying short-term expected returns or risk premia (Fama & French, 1988). These two factors are expected to yield a positive and time-invariant autocorrelation (Koutmos, 1997), however, as shown by LeBaron (1992), non-linear first moment dependencies are reported. In other words, LeBaron’s work presents evidence that autocorrelations of returns tend to increase in periods of low volatility, while decreasing in periods of high volatility. Thence, non-synchronous trading and risk premia cannot be the only explanations to return autocorrelations.

One of the first models that attempts to explain the autocorrelation properties on stock returns is developed by Cutler et al. (1990). They follow the framework proposed by De Long et al. (1990) and create a model in which feedback traders coexist with rational traders. Building upon Cutler et al. (1990), Sentana and Wadhwani (1992) studied the role of positive feedback trading in the U.S. stock market and found strong evidence of positive autocorrelation of stock returns in periods of low volatility, but a tendency to a negative autocorrelation in periods of high volatility. Sentana and Wadhwani’s (1992) finding on the inverse relation between autocorrelation and volatility is consistent with De Long et al. (1990). This relation corresponds to positive feedback trading strategies, i.e. buy winners and sell losers when the market is agitated. Moreover, as arbitrage is risky and costly, noise traders are expected to exert a higher degree of influence on the market in periods of high volatility, thus fully driving stock returns autocorrelations (Koutmos, 1997).

6.3.3. Feedback Trading and Bitcoin

Well-established literature on positive feedback, sentiment, and Bitcoin is very scarce. Since Bitcoin is a recent topic and the Bitcoin Fever aroused recently in 2017, data that would be most relevant to behavioural research is limitedly available. The general interest on this matter, however, is increasing as cryptocurrency markets display intriguing price dynamics that could provide interesting information on the behaviour of investors.

Although positive feedback trading and herding are not synonyms, literature has commonly linked these. Herding is understood as a phenomenon in which people imitate or follow the acts of others collectively and, likewise, has been highly related to the largest movement in financial markets such as the tulip mania or the recent financial crisis in 2007 (Bouri, Gupta, & Roubaud, 2018). Although herding still remains broadly unexplored in the cryptocurrency markets, Bouri et al. (2018) analyse the level of herding behaviour in this area and contribute to the field from a more behavioural perspective. Following the CSAD model from Chang et al. (2000), they find a high degree of herding behaviour in cryptocurrency markets, which in turn may suggest a large number of noise traders subject to behavioural heuristics and biases whose decision are not supported by fundamentals. Bouri et al. (2018) identify the lack of regulation as one of the drivers of speculation and the reason for a majority of noise traders. An increase in regulation could therefore serve as a way to attract more rational traders and institutional investor that would potentially reduce speculative activities to certain extent. This topic will be further developed in the next sections.

6.4. On the Link Between Feedback Trading and Sentiment

Sentiment and positive feedback are closely related terms, and it is thus surprising that literature has not paid stronger attention to the link between these two factors. Recent work by Antoniou et al. (2010), Lemmon and Ni (2010), and Blasco et al. (2012) links sentiment to terms such as herding, speculative trading, or profitability of momentum, which are terms often identified as positive feedback trading.

One of the few researchers investigating sentiment and feedback trading, Kurov (2008), finds a positive relation between sentiment and the level of positive feedback trading experienced in the market. He argues that the intensity of positive feedback trading increases with sentiment, therefore we can conclude that it is, at least partially, driven by sentiment. Building up upon Kurov’s (2008) approach, Hu et al. (2015) examine the level of positive feedback trading for a microstructure context and find further evidence that positive feedback increases following high levels of market sentiment. Yang and Zhou (2015) studied the combined influence that both, sentiment and feedback trading, have on asset prices. They find that these factors significantly influence excess returns, supporting the idea of fundamental price deviations under these conditions.

All in all, feedback traders who believe in non-fundamental signals obtained from technical analysis or heuristics, are likely to trade upon sentiment-driven expectations entirely based on prices going up (optimism) or down (pessimism). Therefore, feedback traders' ultimate trading decisions are determined by sentiment (Chau, Deesomsak, & Lau, 2011).

7. Analysis of the Bitcoin Market

As we have established in the previous sections, positive feedback mechanisms and sentiment are apparent drivers of bubble creations and subsequent crashes. Numerous securities in the stock markets show positive returns throughout their existence. This phenomenon, on its own, does not necessarily imply that feedback mechanisms are present in these markets. We understand that more factors are necessary for feedback mechanisms to take over and create fertile ground for bubbles and the deviation of prices from fundamental values. The existence of noise traders that base investment decisions on sentiment is one of the key facilitators of speculative bubbles. In this section, we analyse the Bitcoin market with respect to noise traders and argue that Bitcoin markets indeed exhibit signs of these.

The maximum supply of Bitcoin is capped by the system, but the daily trading volume depends upon the willingness of investors to buy and sell. In this regard, demand profoundly depends on the investors' expectations of future growth; drivers of investor demand thence become a key element to understanding its volatility and price formation mechanisms. In spite of the general categorisation of investors into rational or irrational traders, cryptocurrency markets, and Bitcoin in particular, have attracted the attention of a number of diverse investors who have been drawn to these markets for different reasons. Some of these investors have been labelled short-term focussed, trend chasers, noise traders or speculators (Kristoufek, 2013). As prices grew, more institutional investors showed interest in Bitcoin. The market, however, still demonstrates some limitations and pitfalls that might discourage institutional investors from entering Bitcoin markets. For this reason, Bitcoin markets present a unique opportunity to investigate the effects of sentiment and feedback trading.

7.1. New Era Thinking

Speculative market expansions and bubbles generally begin with a new opportunity or expectation (Sornette & Cauwels, 2015). According to Sornette and Cauwels (2015), such factors may emerge in the market in the form of a new breakthrough technology, the access to a new type of market, or even a new trading opportunity. Shiller (2015) provides further support for this statement as he associates speculative market expansions with a general public perception of a more positive or less risky future, an expectation of a brighter future. These ideas have commonly been referred to as "new era" (Shiller R. J., 2015) and are influenced to a large extent by investors' sentiment. To recall

Section 6.2., we understand sentiment in this context as the belief about future cash flows not justified by information at hand.

As indicated by Sornette and Cauwels (2015) as well as Shiller (2015), markets that raise the public's expectation of their future prospects tend to provide unique investment opportunities or disruptive technology. In this regard, both Bitcoin and the Blockchain exhibit all mentioned mechanisms: it is a whole new ground-breaking technology with the potential to disrupt the financial sector, brings a whole new market with new products, provides different kinds of trading opportunities and traders from a worldwide perspective, and, lastly, Bitcoin has managed to gain sufficient media attention to be considered one of the most disruptive financial opportunities of the past decade. Similar to the emergence of the Internet in the 90s, when people believed that such technology would boost the productivity of economies (Shiller R. J., 2015), Bitcoin constitutes a disruptive idea that has changed the financial industry and accelerated the process towards a networked business environment (Mai, Shan, Bai, Wang, & Chiang, 2018) (Helbing, 2014).

As Bitcoin prices increased throughout the 2010s, media attention on this phenomenon increased as well as the research provided by numerous anonymous analysts (Andreessen, 2014). Idealists envisioned it as a revolutionary way moving against establishments, whereas politicians and governments saw the potential threat it poses and raised concerns about the levels of speculation in cryptocurrency markets and underlying crime. In the meantime, technology specialists are astonished by the promising opportunities and see major potential in the technology around cryptocurrencies and the Blockchain. More and more Bitcoin enthusiasts are attracted to the market envisioning a global unlimited use of digital currencies and, with them, new investors attracted by the return prospects of Bitcoin enter the market.

Driven by cryptocurrencies' potential for quick profit, more entrepreneurs are incentivized to launch new digital currencies through Initial Coin Offerings (ICO). Such ICOs are increasingly becoming a suitable way of raising funds for new start-ups (Darrell, 2018) as the dollar volumes raised increased considerably (Figure 3). ICOs represent a revolutionary and controversial way of raising funds, as they generally do not require companies to give up equity. Instead, people buy the electronic coins, thereby directly becoming clients of the company and own their products (Ante, Sandner, & Fiedler, 2018). Investors feel attracted to new cryptocurrencies with the aim of finding 'the next Bitcoin' and find ICOs a suitable opportunity. A term describing this behavioural phenomenon is known as FOMO (Fear of Missing Out). It is therefore not surprising that the most successful investments in 2017 were those directed or regarded to Blockchain platforms (Sankaran, October 19, 2018). However, as the fever for adopting new electronic coins increases, bitcoin prices and the level of funds raised by ICOs lead to more and more concerns. A study published by Ernst and Young in 2017 (Sankaran, October 19, 2018), analysing the top ICOs and representing the 87% of total funding, found high risks of fraud and other major issues underlying ICOs funding practises. As of September 2018, the prices of 86% of the new digital currencies created in 2017 were below its listing price level, while 30% lost practically all their value.

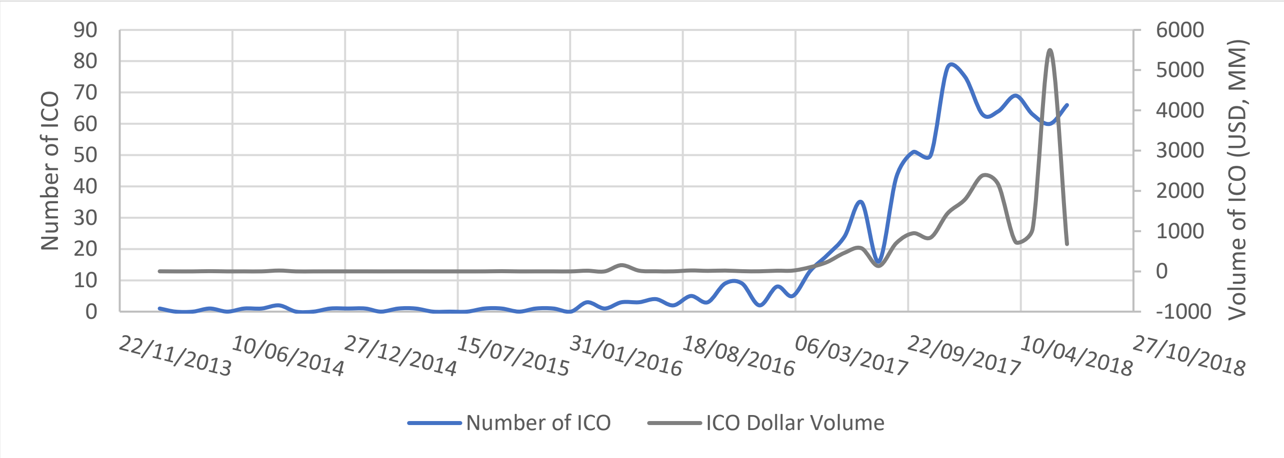

Figure 3 – Total number and dollar volume of monthly ICOs

The similarities of Bitcoin markets to past events of irrational exuberance received considerable attention in behavioural finance literature. Comparing the price evolution of Bitcoin to the speculation during the dotcom bubble makes the similarities even more apparent. During the dotcom bubble, investors poured large amounts of money into new internet companies with the expectation of future profits (Shiller R. J., 2015) (Janeway, 2012), something that resembles the situation of digital currencies and its ICO process. One peculiar similarity of Bitcoin and the dotcom bubble is the popularity of Bitcoin and Blockchain as part of company names, supposedly to boost the stock prices of these companies. Some examples of this are companies such as Tulip BioMed Inc or JA Energy, which changed their name to Bitcoin Services Inc and UBI Blockchain Internet Ltd respectively, experiencing large abnormal positive returns after the modification, and suffering a rough correction back down afterwards (Figure 4) (Detrixhe, 2018). The most striking fact about it is that none of these companies' activities were related to Bitcoin or Blockchain. Intuitively, this reflects the level of exuberance experienced in the markets towards these products.

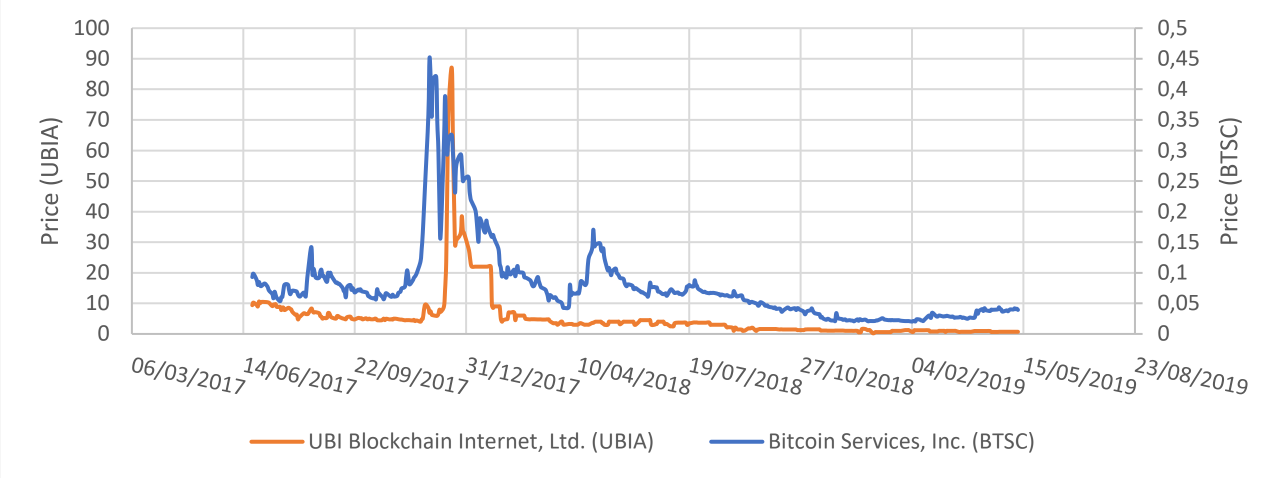

Figure 4 – UBIA and BTSC

Instead of solely focusing on the market evidence of irrational exuberance, we should pay attention to the characteristics that make Bitcoin and the Blockchain unique, as especially the latter represents one of the most promising and disruptive technologies of the future (Ante, Sandner, & Fiedler, 2018). Some proponents envision Bitcoin as becoming an all-purpose payment method which ideally should be utilised no different from any other Fiat currency (Böhme, Christin, Edelman, & Moore, 2015). The advantage of Bitcoin as a generally accepted currency would not only be a common worldwide payment method free of regulation, but also reduce the costs of international payments due to lower commissions. Internationally, this constitutes a big advantage as commissions are traditionally high. In local markets, however, it seems to be only a vague reason for justifying the usage of Bitcoin as traditional ways of payment are equally cheap. What is most striking about Bitcoin is that, for the first time, it allows parties to transfer money without the existence of a centralized authority, i.e. it leaves banks out of the equation. These decentralized systems give way for users to transfer a portion of digital property to another user in a legitimate and safe way without being questioned (Andreessen, 2014) (Böhme, Christin, Edelman, & Moore, 2015).

7.2. The Effect of Massive Social Media and the Internet

Relevant events in the market related to hysteria and euphoria only occur if there is a common stream of thinking or feeling across a large number of people, so that their decisions are capable of affecting the market (Shiller R. J., 2015). Historically, and even more so since the introduction of the internet, newspapers, magazines and all other forms of media have reported on the big catastrophes in financial markets. Over time, as the relevancy of financial markets increased, the attention of the media to financial markets increased as well, and the competition for reaching the highest number of listeners, readers, or users pushed them to create the most interesting news that had and have the best word-of-mouth potential. Even though media commonly claim general objectivity in their description of events, they exert considerable influence on society by potentially spreading sentiment thence possibly influencing investors' attitude towards the market (Shiller R. J., 2015) (Taleb, 2007). Nowadays, with the massive use of social media platforms, and the easiness of accessibility of local and international news, the risk of media influence on sentiment is an even more pressing challenge.

Considering Bitcoin as a potential currency, its value is not derived from gold or government fiat, which makes its valuation highly complicated and left to whatever value investors assign it (Mai, Shan, Bai, Wang, & Chiang, 2018). In this sense, discussions on social media platforms, where investors can engage in conversations and provide feedback about the situation of the market, should have an impact on the price dynamics of Bitcoin (Mai, Shan, Bai, Wang, & Chiang, 2018). If we assume that the Efficient Market Hypothesis (Fama, 1970) is applicable to Bitcoin markets due to its resemblance to stocks markets (c.f. Section 4.2.), price fluctuations should follow new information. Nowadays, this new information usually comes through social media and Web 2.0 applications (User-Generated Content platforms), which have disruptively changed the way users interact (Gallaugher & Ransbotham, 2010).

Intuitively, User-Generated content platforms could therefore predict Bitcoin price movements and trading volume to some extent (Mai, Shan, Bai, Wang, & Chiang, 2018). New information can be disclosed online, such as regulative measures or even hacking attacks, potentially affecting the price of Bitcoin. Further, online debates can provide a good sense of the level of sentiment in the market and how people react to the release of new pieces of Bitcoin-related information. Lastly, speculative investors tend to herd and follow trends (feedback trading). In accordance with these statements, Mai et al. (2018) find a strong positive correlation between sentiment and Bitcoin prices. Furthermore, they find that disagreement on social media is associated with increases in future trading volumes. They based their investigation on text mining analysis of the most representative Bitcoin online communities (for example discussion forums) and all the tweets that included the hashtag '#Bitcoin'. They find significant results that support the idea of bullish posts followed by positive returns and vice versa. Furthermore, disagreement seems to encourage trading. This goes along the lines of Lebaron (1992), and Sentana and Wadhwani (1992) who likewise find that disagreement induces a higher level of volatility as well as a negative level of autocorrelation in asset returns.

The fact that everyone can potentially participate in online discussions on the value of Bitcoin and influence the opinion of others, combined with the predominance of individual investors, seems to contribute to the high volatility of Bitcoin prices. The price formation of Bitcoin, however, still remains an incognita which highlights the importance of taking sentiment into account (Kristoufek, 2013) (Ciaian, Rajcaniova, & Kancs, 2016). Individual investors around the globe are nowadays not only able to access social media content in order to collect information about the general public's attitude towards Bitcoin, but they can also independently search to understand what Bitcoin is and how to invest. Although the understanding of the underlying technology is complex, acquiring a Bitcoin or a portion of one is easy. Anyone with a computer and access to the internet can buy Bitcoin. Recently, several studies have found a strong relationship between Google Trends and Wikipedia searches and prices in stock markets, and Bitcoin markets in particular. On one hand, Ciaian et al. (2016) argue that Wikipedia searches have an influence on the supply and demand of the electronic currency, subsequently affecting short-run price movements, while no significant long-term influence is found. On the other hand, Kristoufek (2013) finds a relationship between Bitcoin prices and Google searches. The number of related search queries tends to move along with prices and vice versa. This is in line with the ambiguity of fundamentals in Bitcoin prices, further implying the existence of speculation and positive feedback trading in Bitcoin markets (Kristoufek, 2013). According to Ciaian et al. (2016), the role of these two factors in the price formation of Bitcoin indicates a high degree of noise traders as the type of individuals seeking information about Bitcoin on Wikipedia is not likely to be very knowledgeable about Bitcoin, since these sources contain rather basic information.

7.3. Regulation

Compared to other traditional payment methods or to classic financial markets, Bitcoin lacks a governance structure apart from its supporting software (Böhme, Christin, Edelman, & Moore, 2015). In line with the original idea and its decentralized system, Bitcoin has managed to stay away from governments' control and regulatory systems; this aspect, however, has brought both supporting and resisting movements. On the one hand, Bitcoin extends a stream of libertarianism that rejects the role of governments, and associated overseeing of communications and their inflationary controls (Böhme, Christin, Edelman, & Moore, 2015) (Lan Ju & Tu, 2016). On the other hand, another stream of academics and politicians warns about the vulnerability of Bitcoin markets to speculation, denounces misinformation, and publicizes scepticism about its potential to become a real currency (Glaser, Zimmermann, Haferkorn, Weber, & Siering, 2014). Regardless of its utility and potential, the lack of regulation combined with the uncertainty about its intrinsic value could explain the volatility levels in Bitcoin markets and its susceptibility to speculation and bubbles (Grinberg, 2011).

Bitcoin is a homogeneous good that is traded on different global markets. Intuitively, prices across these markets should adhere to the law of one price (LOOP); inconsistencies in prices, however, are found from one market to another. Therefore, if price differences are found, they must be associated to certain features of the exchange on which they are traded (Pieters & Vivanco, 2017). Even though Bitcoin markets lack a regulatory body, some local measures have been implemented since 2014 that affect specific countries. For example, the banning of Bitcoin in 2014 in Ecuador or the implementation of taxes and licences to trade in Asia (Pieters & Vivanco, 2017).

Governments generally justify their intention to regulate cryptocurrency markets with the need for consumer protection as there is no protections of users against unauthorized transfers (Böhme, Christin, Edelman, & Moore, 2015). This became a more central topic of discussion after the infamous failure of the Bitcoin exchange market Mt. Gox in February 2014, when more than 300 million USD of Bitcoin value were lost in a security breach (Higgins, Coindesk, 2016). This fact seems to have been unnoticed or ignored by investors as prices kept rising despite this incident.

Apart from the apparent uncertainty about price formation, the lack of regulation may be a key motivation for institutional investors to refrain from participating in Bitcoin markets. This in turn may explain the level of speculation and volatility in the market as (individual) feedback traders are more subject to sentiment and short-term returns than institutional traders. We find several reasons related to regulatory issues that may prevent institutional investors from entering Bitcoin markets.

Trading practises

Institutional investors generally employ more complex trading strategies such as volatility trading and short-selling, whereas non-institutional investors tend to apply basic buy-and-hold strategies (Baur, Hong, & Lee, 2018). Unfortunately, Bitcoin markets did not allow such complex trading strategies for most of the time as hedging opportunities were completely inexistent until the introduction of derivatives to mainstream markets in December 2017, when BTC futures were introduced to CME (CME Group Inc, 2019) and CBOE, two major U.S. exchange markets with a proper regulatory framework protecting institutional investors (Köchling, Müller, & Posch, 2018).

Institutional investors have progressively exposed themselves to Bitcoin markets through the purchase of futures; they are, however, not buying the underlying asset (Renaudin, 2018), which lowers the expectations of an upcoming rationalization of prices.

Counterparty risk

In spite of its general acceptance as a secure payment method, Bitcoin has a substantial record of hacks and thefts. This potentially further intimidates institutional investors as they usually manage larger amount of money in the markets. The most famous incident is the previously mentioned MT.Gox hack in 2014. Numerous other cases, however, have further occurred such as the Bitfinex exchange market theft, where 60 million USD worth of Bitcoin were stolen (Higgins, Coindesk, 2016).

Moreover, some exchanges have experienced technical issues that were not handled appropriately. For instance, on January 11, 2018 a two hours system upgrade was announced, during which investors were denied access. Eventually, the system upgrade lasted two days (Dinkins, 2018). In the meantime, investors were trapped in a bear market without the possibility to take action.

These fundamental risks are unacceptable to take for financial institutions who require guarantees on the execution of their transactions, as well as an insured, safe deposit for their money and investments. This is particularly important when operating in markets as volatile as Bitcoin markets.

Money laundering activities

The anonymity feature of Bitcoin markets represents a challenge in the fight against money laundering and facilitates the existence of illegal activities as individuals can order illegal goods online that are then delivered to their addresses without seeing the trade partner and without knowing their names (Morselli, Decary-Hetu, Paquet-Clouston, & Aldridge, 2017). Undoubtedly, anonymity and decentralization have made Bitcoin become an attractive alternative means of exchange for criminals (Brown S. D., 2016).

For non-electronic-coin exchanges it is mandatory to register all users of their platform in order to prevent money laundering or other criminal activities. Although some implementations of Know-your-customer measures have been carried out in the U.S. and China, there are still plenty of other cryptocurrency exchange markets where traders are completely untraceable. In this regard, Foley et al. (2019) estimate that one quarter of Bitcoin transactions are linked to criminal activities, being considerable drivers of Bitcoin prices. In this case, several problems for institutional investors arise. On one hand, investors might be ethically concerned about the fact that the value of their investment is connected to and influenced by illegal activities, which in turn would render them indirectly in criminal activities. This is unacceptable for institutional investors who are exposed to media. On the other hand, upcoming anti money laundering regulation in some of the Bitcoin markets could further boost the price and encourage the emergence of unregulated markets, thus undermining the more transparent markets.

Implemented and upcoming regulation

Throughout the history of financial markets, large crashes have provided opportunities for academics and politicians to further understand the influence of rules, investors, and arbitrage in prices. New events with different characteristics emerge occasionally. New measures are often launched to the market, ranging from increasing market control to innovative monetary policies that attempt to reduce the level of speculation in the market and mitigate the effects of financial crashes. Most of these measures, however, are implemented only after the crashes have already had a strong impact on society (learning process). Bitcoin represents a whole new market under new disruptive technology. Therefore, it should not be surprising that both investors and regulatory organizations struggle to understand it, to propose regulatory measures, and to improve its efficiency.

The European Union Commission is already developing a new anti-money laundering regulation (AMLD5) that will deal with cryptocurrencies and will have an international scope (Houben & Snyers, 2018). There is no global approach to taxation and it this remains an open question. For instance, as discussed in Section 4, the European Union declared Bitcoin trading not subject to VAT, whereas the U.S. considered Bitcoin as a property rather than a currency with its consequent tax on capital gains (Norry, 2018).

In the light of the issues discussed in this section, regulation is essential for price stability. Depending on the scope of an increasing regulation, it could potentially damage short-run Bitcoin prices. It should not, however, undermine its long-term value. An increase in stability in Bitcoin prices could bring more suitability for it to be used as a currency. It could, however, also hamper some of its original benefits that attracted the initial followers of the electronic coin.

7.4. Trust

The value of currencies generally depends on peoples' trust. This trust is not always constant as we see global crises or major events affecting their value constantly. Moreover, today´s rapid technological development poses a bigger risk to the stability of global economies (Jacobs & Mazzucato, 2016). Government or economic instability will certainly affect the value of local currencies as trust levels decrease. Bitcoin introduced a completely different scenario as governments do not have power over its prices. Moreover, opposite to fiat currencies, the system that surrounds Bitcoin is immutable which potentially gave a bigger sense of trust to the general public.

The creation of Bitcoin in 2008 followed the most recent financial crisis. A large number of banks defaulted across the world and Central Banks had to come to their rescue at the expense of tax payers', i.e. individuals', money. The financial sector and monetary systems' fragilities were exposed. As a consequence, mistrust towards fiat currencies aroused. Fiat currencies are predominant in the world nowadays, and their value is only backed by trust in governments, which explains why historically currencies were linked to gold. If trust in governments decays, people will look for alternatives.

This mistrust is especially found in those developing countries that have experienced constant struggles with their local currencies. These countries usually look for new places to store their value and found in Bitcoin a promising and viable alternative (Stevis-Gridneff & Kantchev, 2018). However, this does not explain the interest of developed countries in the electronic coin, which might be subject, for instance, to speculation and media exposure among other influences beyond its function as a mean of exchange. This notion further supports the classification of Bitcoin as an asset (c.f. Section 4.2.).

Whether the creation of Bitcoin was a consequence of the crisis has been largely discussed. Whereas some claim that Bitcoin is the final outcome of years of trying to create a successful electronic coin (Hankin, 2018), others state that Bitcoin is the consequence of the 2007-2008 crisis (Halaburda, 2016a). In conclusion, Bitcoin, and cryptocurrencies in general, may help to enhance stability in systems through trust surges as the underlying innovative technology is reliable. The current volatility in cryptocurrency prices, however, undermines any stabilizing effect of trust.

8. Methodology

In this section we describe our research approach as well as the analytical steps towards assessing feedback trading in Bitcoin markets. In Section 8.1 we introduce the general philosophy of research. In Section 8.2. we then introduce the methodology of constructing the Baker and Wurgler (2006, 2007) sentiment index, including a detailed description of the conception of the six proxies to investor sentiment. In Section 8.3. we detail the feedback trading model as proposed by Sentana and Wadhwani (1992), as well as its extensions allowing for investor sentiment (Chau, Deesomsak, & Lau, 2011).

8.1. Research Methodology

In this section we explain the theoretical methodology we follow throughout this thesis. First, we elaborate on our perception of reality that determined the generation of knowledge. For instance, we follow an objective view of reality in which social entities exist independently from social actors.

Our analyses and the interpretation of results are influenced by our perception of reality and determined by our approach to acquiring knowledge. Acknowledging the decisions taken, we expect to provide a deeper understanding of the research approach taken and of the reliability of our conclusions.

8.1.1 Research Philosophy

Our take on research philosophy entails important implications on how we see reality (Ontology) and our understanding of the relationship between knowledge and how it is generated (Epistemology) (Saunders, Lewis, & Thornhill, 2009). Which approach to philosophy is preferable depends on what kind of research question we strive to answer. In the following subsections we outline the ontological position. We do not engage in a conversation about which philosophy is superior, as no research approach is inherently better than others; instead, we define our research philosophy and develop our subsequent strategy which delineates our research approach taken on in this thesis.

Ontological Position

Ontology is concerned with the nature of reality and makes important assumptions about the way in which the world works (Saunders, Lewis, & Thornhill, 2009). We presuppose that social phenomena are independent from social actors, and that these social phenomena create patterns that are yet to be discovered. We therefore follow an objective view of reality. We argue that Bitcoin markets, and financial markets in general, follow a general representation in which the demand of investors is characterised by a certain structure. In contrast, a subjective or constructive point of view asserts that phenomena are socially constructed and constantly changing (Saunders, Lewis, & Thornhill, 2009). Applying this type of research allows us to study certain variables that we believe to affect investors, and to study not only their existence and magnitude, but also how they interact with one another.

Epistemological position

Epistemology deals with what is acceptable knowledge in a field of study, or what is most decisive (Saunders, Lewis, & Thornhill, 2009). The position we adopt, already bounded by our ontological choice, is going to determine how we collect and analyse the facts under investigation. At last, epistemological points of view are classified in terms of whether methods used in natural sciences are applicable to social sciences as well.

Throughout our thesis we investigate the effect of different concepts (sentiment and feedback trading) that arise and coexist in financial markets and investors' minds, but that we cannot directly perceive. Instead, the only way we are able to observe them is by their consequences in real life. We thence establish that acceptable knowledge must be based on empirical data that reflect and make such findings observable. In this regard, we agree with critical realism as our philosophical position and with authors such as Bhaskar (1989) who state that we are only capable to understand what happens in the social world if we understand the social structures that enable the phenomena that we are studying. In other words, we see reality as a consequence of social conditioning.

Consistent with our realistic point of view, we are not testing the existence of sentiment and feedback trading in Bitcoin markets; our point of interest rather lies in the relationship between these variables and Bitcoin price volatility. Moreover, the fact that we view data as objective is a central element to perform our analysis externally to our own values and likely biases.

8.1.2 Research Approach

Our research approach determines whether our project involves theories or theories are to be constructed from our observations (Saunders, Lewis, & Thornhill, 2009). We build upon existing theories of investor behaviour and decision making that establish a framework and set the basis for the application of our chosen model. We therefore follow a deductive approach. We base this thesis on theories that determine the existence of rational and feedback traders behaving in certain ways that will affect the market under investigation and shape their demand of securities.

An additional important feature of a deductive approach, which we successfully implement, is that the concepts that we take as variables need to be operationalised to allow for quantitatively measuring facts (Saunders, Lewis, & Thornhill, 2009). Firstly, we build a composite index to reflect sentiment following Baker and Wurgler (2006). This provides a relative measure of sentiment that we can use in our analysis. We then determine the level of feedback trading in the market as a parameter that would indicate the presence of both positive or negative feedback and its direction relative to sentiment and volatility. To advance the quantification of the level of sentiment, we follow the principle of reductionism. To this end, we reduce investor sentiment by assigning dummy values of 1 and 0 to optimistic and pessimistic states, respectively. This is done as problems are usually better understood when reduced to the simplest possible elements (Saunders, Lewis, & Thornhill, 2009).

8.1.3 Research Strategy

By research strategy we refer to the plan we follow in order to answer our research questions (Saunders, Lewis, & Thornhill, 2009). Our strategy is determined by the nature of our research question, the objectives we want to meet, available resources and the extent of existing knowledge in the field of study (Saunders, Lewis, & Thornhill, 2009). It is therefore important to note that the conclusions we draw are only observation for one specific research design and do not necessarily hold in a universal context.

According to Robson (2002), a strategy for conducting research that involves an empirical investigation of certain real-life contemporary circumstances using several sources of evidence is denominated as a case study. This definition seems to depict the strategy we follow as we investigate the relatively young Bitcoin phenomenon employing numerous sources of information and empirical data on Bitcoin returns and macroeconomic variables such as DataStream (Thomson Reuters, 2019). In contrast to other strategies such as experiments, where the subjects under study are under a controlled environment, in our case the boundaries between the aspects under study and the context in which they are being studied are not obvious.

This case study approach helps us to answer our research questions as well as learn about the context in which the thesis is constructed. Also bettering the understanding of the study context is a motivation to use case study strategies in explanatory and exploratory research (Saunders, Lewis, & Thornhill, 2009).

8.1.4 Method Choice

The choice of our research method defines the techniques and the procedures to be used to analyse our data. The research methods are generally divided into qualitative or quantitative depending on their emphasis on numerical or non-numerical data. Quantitative is used as a reference to any kind of data collection and analysis process that generates and uses numerical data, whereas qualitative generates or uses non-numerical data (Saunders, Lewis, & Thornhill, 2009). To provide a scientific answer to our research questions, the access to adequate empirical data with certain levels of significance and representativeness is a key task. We follow a quantitative method approach to address the research questions.

Again, when choosing the research method, the philosophical position plays an important role since the method selected may imply a certain view of reality (Saunders, Lewis, & Thornhill, 2009). The fact that we follow a philosophical standpoint of critical realism makes us detached from the research question and thus able to provide an objective point of view. Moreover, the application of scientific techniques to find new knowledge by the use of well-established economic models and statistical methods further contributes to answering our research questions.

8.1.5 Time Horizons

As previously stated, we investigate the relationship between sentiment, feedback trading and volatility. Since these variables are not observable at any point of time, we find that a longitudinal study is consistent with the purpose of our thesis.

In line with a longitudinal study type, our work aims to understand how investor trading strategies are affected by other variables present in the market, and how these change over time (Saunders, Lewis, & Thornhill, 2009). As a result, the findings may help to further understand the dynamics in Bitcoin markets and contribute to regulation possibilities and investor protection.

8.2. Sentiment Index

To investigate the relation between investor sentiment and feedback trading in Bitcoin markets, we first need to measure the level of sentiment in the market. We follow the “top-down” and macroeconomic approach to investor sentiment proposed by Baker and Wurgler (2006, 2007). This analysis is market based and targets the measurement of aggregate sentiment and its effect to market returns. In our "top-down" approach, factors such as behavioural biases are considered exogenous. Exogenous factors impacting investor sentiment can, of course, have a repercussion on financial markets. The origination of one factor can lead to a chain of events observed at a specific or every part of that chain. For example, these factors can manifest in the form of observable patterns or mispricing within the selected market-based variables (Baker & Wurgler, 2007).

In contrast to the "top-down" approach, in a "bottom-up" approach one would consider biases implicit in investors' psychology such as confidence or optimism. The market, however, is too complicated to be reduced to a few biases and market imperfections (Baker & Wurgler, 2007) which rules out the possibility of measuring the overall level of sentiment "bottom-up".

8.2.1. Data Presentation and Variables

We construct a monthly investor sentiment composite index based on six market-based sentiment proxies proposed by Baker and Wurger´s (2006). These relate to investors' propensity to purchase stocks (Chau, Deesomsak, & Lau, 2011). The index is based on a Principal Component Analysis (PCA) that captures the common component of our six proxies and takes into account the fact that some variables may take longer to have an impact onto investor disclosure of sentiment.

Instead of focusing on Bitcoin data, we utilise general U.S. market data as a proxy to calculate the index to find a relation between U.S. stock markets sentiment and U.S. Bitcoin markets. Our decision to construct Baker and Wurgler's index utilising U.S. data is motivated by the impossibility of applying it to cryptocurrency markets. We identify mainly two obstacles: (1) Variables in Bitcoin markets that are affected by investor sentiment have not yet been systematically investigated (Eom, Kaizoji, Kang, & Pichl, 2019). (2) Utilising the same proxies for cryptocurrency markets as for U.S. markets is not feasible as not all necessary data is available (c.f. Section 10.4).

The six variables that we utilise as proxies to investor sentiment are 1) share turnover (*turn*), 2) dividend premium (*pdnd*), 3) closed-end fund discount (*cefd*), 4) equity share in new issues (*s*), 5) first-day returns on IPOs (*ripo*), and 6) number of IPOs (*nipo*). A total of 102 monthly observations from July 2010 to December 2018 are retrieved from diverse databases (specified later in this section). In the following, we describe each of the six proxies in further detail.

Share turnover (turn)

Baker and Stein (2004) argue that market liquidity can serve as an investor sentiment proxy in a world with short-selling constraints. They find that when short-selling is costlier than opening and closing long positions, as it is generally the case in markets, rational investors are less likely to exert arbitrage. Irrational investors are, therefore, more prompt to trade and add liquidity to the market when they are optimistic and bet for those stocks with a recent track of positive returns (buying winners). For this reason, high liquidity is considered an indicator of overvaluation as a consequence of optimism (or positive sentiment) from the side of irrational investors.

Market turnover serves as a proxy for market liquidity. Our calculation of turnover is based on the New York Stock Exchange (NYSE) Composite Index log ratio of total market turnover, which is calculated as the dollar value of the trading volume at period *t* divided by the total market capitalisation in the previous period. In line with Baker and Wurgler (2006), this is subsequently detrended by subtracting its five-month-moving-average in order to remove the negative trend found in the time series. Both trading volume and market capitalisation data were retrieved from Bloomberg (Bloomberg, 2019). Turnover ratio at time *t*, denoted as *turn*, is defined by:

$$turn_t = log\left(\frac{Volume_t}{MK_{t-1}}\right) - \frac{1}{5}\sum_{i=t-6}^{t-1} \log\left(\frac{Volume_i}{MK_{i-1}}\right) \tag{5}$$

Where $Volume_t$ represents the dollar volume of all shares traded at time *t* and MK_t represents the market capitalisation at time *t-1* for the NYSE Composite index. Figure 5 depicts the resulting *turn* time series.

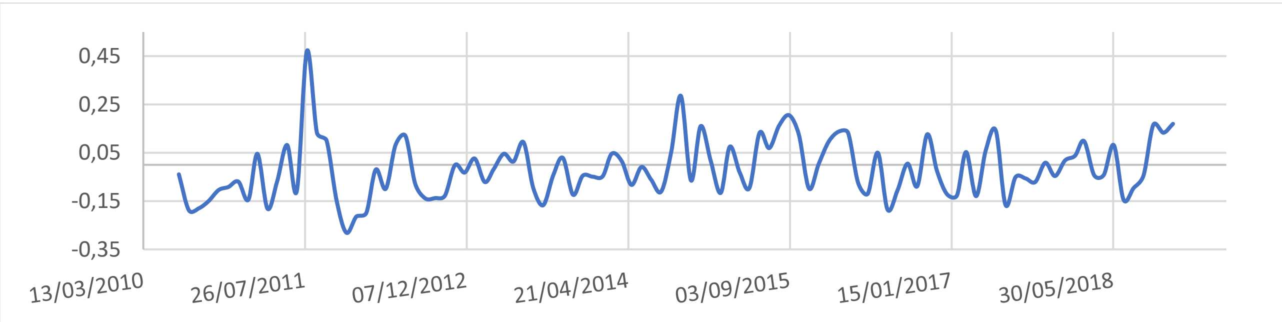

Figure 5 - turn

Dividend premium (pdnd)

Miller and Modigliani (1961) proved the irrelevancy of dividends in the value of shares when markets perform efficiently. In the considered scenario, investors should be indifferent between either capital gains or dividends as the resulting outcome yields the same return. Note that, theoretically, in efficient markets arbitrage ensures that dividends are equal to capital gains in case of no pay-out policy (Miller & Modigliani, 1961).

Baker and Wurgler (2004a) generalise this theory by weakening the assumption of market efficiency and find strong evidence for the importance of dividends for investor valuation, but with different degrees at different times. Moreover, their proxy to dividends suggest that managers cater to investor dividend demand chasing to maximize their stock price. In other words, they pay dividends when investors want dividends, which will subsequently increase the price of the share as a consequence of an increase in demand. They attribute psychological factors, such as perception of safety, and therefore sentiment as a key source of investor demand for dividends. This would explain the fact that investors shift to purchasing dividend-paying stocks when the level of sentiment in the market is high. The predictable income stream for dividend-paying stocks resembles bonds and represents a salient characteristic of safety for irrational traders (Baker & Wurgler, 2004a). Note that this influence is exerted on noise traders, as rational traders are not *directly* affected by exogenous factors.

The proxy used to test their hypothesis is the dividend premium (*pdnd*) and is calculated as the log difference of the average market-to-book ratios of dividend paying and non-paying corporations:

$$pdnd_t = \log\left(\frac{B}{M}\right)_{payers} - \log\left(\frac{B}{M}\right)_{non-payers} \tag{6}$$

Where B/M corresponds to the average book to market ratio of paying and non-paying respectively.

If we assume that investors drag dividend paying stock prices up when the level of sentiment in the market is high, the difference in value derived from the dividend premium will give us an indication of the level of sentiment in the market as dividend-paying stocks will tend to be overvalued.

To calculate this proxy, we use data from 747 organizations that constituted the S&P 500 index during the period of time we consider as an approximation to the U.S. market. We then adjust for those companies that shifted from paying out dividends to not paying and vice versa. The raw data is extracted from COMPUSTAT (Compustat Daily Updates, 2019). Figure 6 shows the time series for the *pdnd* estimation.

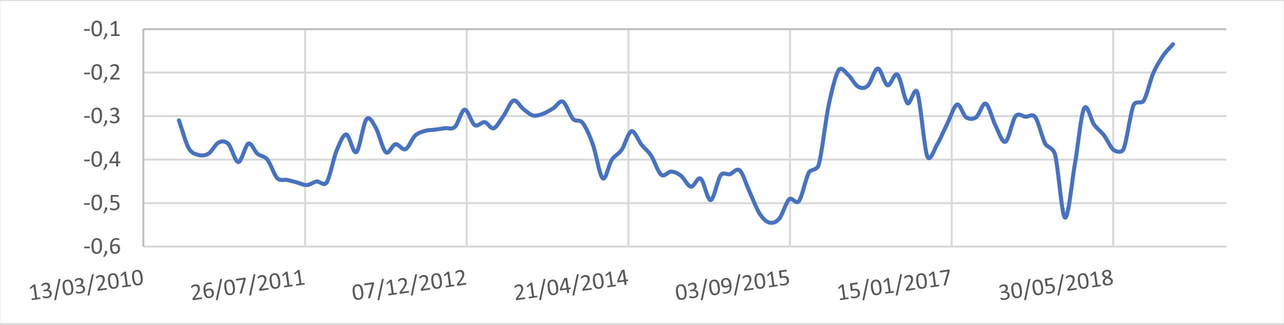

Figure 6 - pdnd

Closed-end fund discounts (cefd)

Closed-end funds are investment companies that issue a certain number of shares that are then traded on the financial markets. Closed-end funds are similar to mutual funds in the sense that they hold other publicly traded securities. Unlike open-end funds the number of shares issued by a closed-end fund is fixed and unchangeable. Investors that look for selling them would therefore have to do so as a bundle for the corresponding price that is being traded instead of redeeming them with the fund for their Net Asset Value (NAV) as it would occur in an open-end fund (Baker & Wurgler, 2007) (Lee, Shleifer, & Thaler, 1991). The closed-end fund discount (*cefd*) is, therefore, the difference between the NAV of the fund´s security holdings and the fund´s market price (Baker & Wurgler, 2007). This difference in value, usually referred to as the closed-end fund discount puzzle, has attracted the attention of many academics that have attempted to find an explanation to this puzzle, which is usually attributed to agency costs, tax liabilities or illiquidity of assets (Lee, Shleifer, & Thaler, 1991).

In this regard, Lee, Shleifer and Thaler (1991), Zweig (1973), and Neil and Wheatley (1998) find that in the case of closed-end funds, fluctuations in investor sentiment will lead to changes in the demand for closed-end fund shares, which will in turn negatively affect the discount. They argue that when closed-end fund shares are held mainly by retail investors, the average discount may function as a sentiment proxy, which will tend to increase when investor sentiment is low. That is, discounts are high when investor feel pessimistic about future expectation and low when they feel optimistic.

Again, the closed-end fund discount is estimated as the average difference in value between the NAV of closed-end fund stocks and their market prices. For our proxy estimation, we take a total of 248 U.S. traded closed-end funds from the Lipper (Lipper, Inc., 2019) lists as reference to select funds. Finally, NAV and market prices are retrieved from DataStream.

$$cefd_t = \frac{\sum_{i=1}^{248} d(i)_t}{N}, \qquad where\ d(i)_t = \frac{NAV(i)_t - Market\ price(i)_t}{NAV(i)_t} \tag{7}$$

Where $d(i)_t$ refers to the discount of fund *i* (i=1, … ,248) at time *t*. Figure 7 shows the time series for the *cefd* estimation.

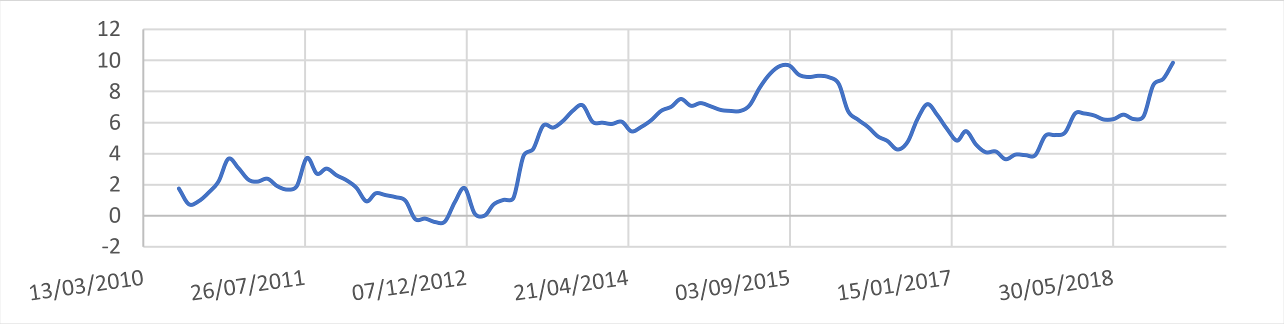

Figure 7 - cefd

Equity Shares (s)

We understand equity shares (*s*) as the value of total equity issues (including IPOs) over the value of total new issues (debt and equity) in the market by all corporations (Baker & Wurgler, 2007). Equity issues are likely a part of the financing strategy of an organization. Modigliani and Miller (1958), again under the assumption of market efficiency, proved the irrelevancy of financing policy for investment decisions. When the market is inefficient, however, as it is observed in reality, financing policy decisions become relevant in various ways. For instance, when stock prices are overpriced, company managers benefit from the issuance of new shares, whereas when prices are low debt issuances are prioritized (Baker & Wurgler, 2000).

As stated before, high investor sentiment will drive stock prices up beyond their fundamental values. Considering this, equity issues tend to occur with a higher frequency when sentiment levels in the market are high since organizations will take advantage of the temporary overpricing of the underlying shares (Baker & Wurgler, 2000). Correlated investor sentiment suggests that other securities will be overpriced in parallel, which will induce other firms to make similar financing decisions (Baker & Wurgler, 2000). We therefore use equity shares as a proxy for sentiment that enters the index with a positive weight.

We calculate monthly equity shares in new issues as defined by Baker and Wurgler (2000), i.e. as the total volume of equity issuances in the previous 12 months divided by the sum of total equity and debt issuances over the previous 12 months:

$$S_t = \frac{\sum_{i=t-13}^{t-1} E_t}{\sum_{i=t-13}^{t-1}(E_t + D_t)} \tag{8}$$

Where E_t stands for equity issues and D_t for debt issues at time *t*.

Monthly data is retrieved from the Federal Reserve Bulletin (Board of Governors of the Federal Reserve System, 2019) and ranges from July 2010 to December 2018. Figure 8 depicts the time series for equity shares.

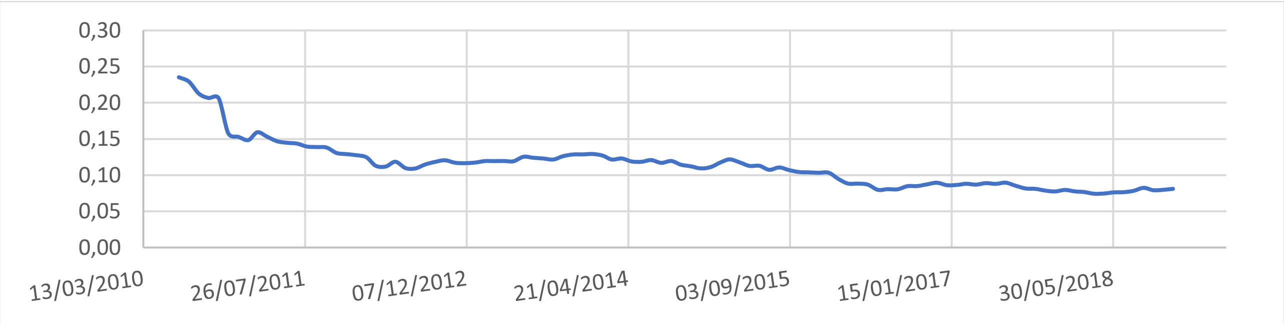

Figure 8 - s

IPO volume (nipo) and first-day returns (ripo)

It is common that Initial Public Offerings (IPO) exhibit abnormal positive returns on their issue day; it stands to reason that investor sentiment possibly plays a role for this phenomenon (Baker & Wurgler, 2007). Researchers have frequently attempted to explain this circumstance and attributed it to information asymmetries and reputation issues between the issuer and the potential investors (Beatty & Ritter, 1986) (Beatty & Welch, 1996). Beatty and Ritter (1986), for example, state that the IPO firm's true value is only known by the issuer, therefore investors require a lower initial price to compensate for the risk taken. In turn, lower initial prices induce a conflict of interest between the underwriter and the issuer, since the underwriter will be incentivized to set a lower initial price in order to reduce the risk of failure.

IPO prices are generally set after consultation with market agents and investment bankers who are well-informed about the situation of the markets. In addition, offer prices are usually released in advance with a subsequent gathering of information about general interest in the stock. These two facts, unfortunately, weaken the two theories about IPO under-pricing presented above.

The '*true*' reasons behind the under-pricing of IPOs yet remain a puzzle (Baker & Wurgler, 2007) . Interestingly, Baker and Wurgler find that IPO first day returns are not guided by idiosyncratic factors, but by the extreme unpredictability of investor sentiment that firms will seek to take advantage of. Furthermore, Ritter and Welch (2002) and Ljungqvist et al. (2006) prove that the information asymmetry theory is not enough to explain this phenomenon and unveil investor sentiment as an important driver of IPOs large first day returns. Generally, investment bankers talk about "windows of opportunity" regarding IPOs when the level of sentiment in the market is high, which usually translates into a successful IPO (Baker & Wurgler, 2007). This might explain the fluctuations in the total number of monthly IPOs found in our time series (See Figure 9).

Following this reasoning, we utilise first-day returns on IPOs (*ripo*) as a proxy to sentiment that we expect to enter the index with a positive weight, coherent with the monthly number of IPOs (*nipo*). The data was retrieved from Jay Ritter's website (Ritter J. , 2019), which is also used by Baker and Wurgler (2006, 2007) as a reliable source to estimate their original sentiment index.

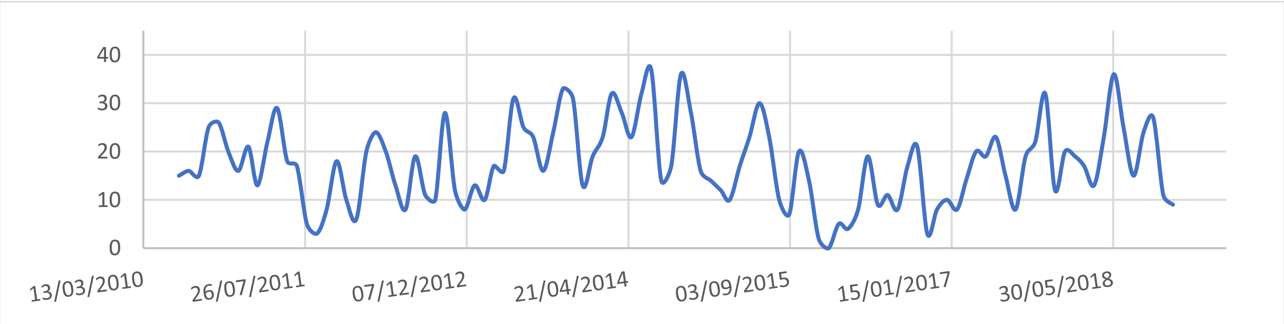

Figure 9 - nipo

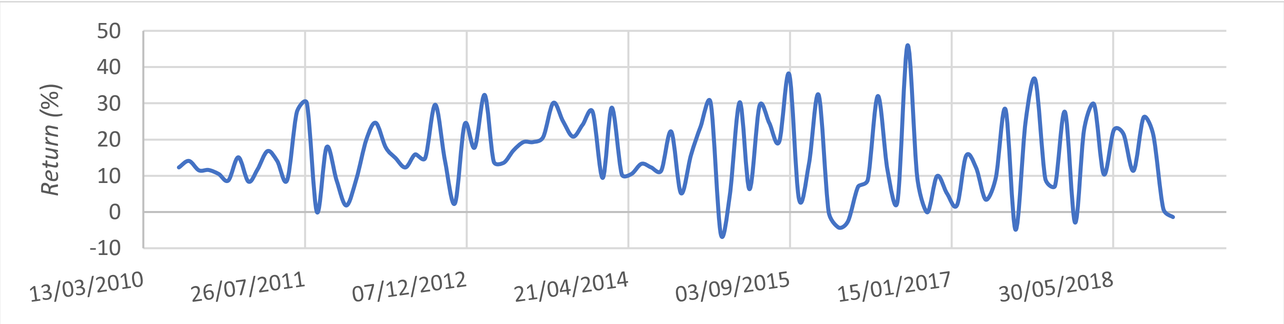

Figure 10 - ripo

Removal of idiosyncratic component

Even though these six variables tend to be affected by psychological factors, each of them is likely to comprise a sentiment component as well as an idiosyncratic component (not related to sentiment) (Baker & Wurgler, 2006). Presumably, our variables reflect economic fundamentals that are subject to economic fluctuations to some extent. We are, however, solely interested in detecting movements in the proxies that cannot be attributed to fundamental factors. The work of Baker and Wurgler emphasises the noisy nature of proxies to investor sentiment and attempts to remove a large portion of such.

Consistent with Baker and Wurgler (2006), to construct an index that differentiates between sentiment components and business cycle components, we regress each of the six raw proxies, lagged ('*yesterday's value*') and lead ('*today's value'),* to six different macroeconomic indicators (c.f. Section 8.2.2). The indicators selected, following Baker and Wurgler (2006, 2007), are the industrial production index (*indpro*), growth in consumer durables (*consdur*), growth in consumer non-durables (*consnon*), growth in services (*consserv*), growth in employment (*employ*), and the consumer price index (*cpi*) for the U.S. market. We then utilise the residuals obtained from the regressions as our sentiment proxies. The data of the six macroeconomic variables have been obtained from the Federal Reserve of Economic Data (Federal Reserve Bank of St. Louis, 2019) for a total of 102 monthly observations from July 2010 to December 2018.

8.2.2. Composite Index Construction

In this section we elaborate on the methodology employed by Baker and Wurgler to develop their sentiment index. In Section 8.2.1, we described the variables the index is constructed from and the sources of the data needed to derive these variables. When constructing the index of investor sentiment from the six proxies to sentiment one must bear two concerns in mind. First, in accordance with Baker and Wurgler, we expect that the six proxies contain both, a component indicating investor sentiment, but also an idiosyncratic component that is not indicative of sentiment. We remove this component by regressing the proxies to the six macroeconomic variables presented in the previous section. Then, we construct two indices in parallel, one for the raw proxies and one for the residuals of the regressed proxies. The second issue concerns the relative timing of the variables; do the variables affect investor sentiment immediately or is the response lagged? For instance, the effect of *nipo* appears to lag compared to first-day returns (Ibbotson and Jaffe (1975), Lowry and Schwert

(2002), and Benveniste et al. (2003)). We therefore determine for each of the six proxies whether its lead or its lag is most suitable to proceed with.

How can we segregate investor sentiment, the component we are interested in? If we assume that the six proxies are indicative of the same aggregate sentiment, one could attempt to isolate the common component of the proxies. Baker and Wurgler apply a PCA to separate the most informative component of the six proxies. First developed by Pearson (1901), PCA is also a helpful tool to reduce the dimensionality of data.

We could describe each month's investor sentiment by simply stating the value of each proxy, but it would be considerably more convenient to express sentiment as a single value. For example, in January 2017, we observed 10 IPOs (*nipo*), with an average first-day-return (*ripo*) of 5.10%, and a NYSE share *turn* of 0.09. While that collection of values gives a rough indication of the aggregate sentiment in the market, it is rather difficult to make sense of six different values. Aggregating these six values into one instead, facilitates the interpretability of sentiment, particularly when comparing sentiment over time.

Intuitively, six values yield more information that one value. When reducing dimensionality, we wish to lose as little information as possible. PCA is a useful compromise between dimensionality and information as it preserves the critical information without reducing the inputs, or features (our six proxies). It constructs a variable that reflects all six variables in such a way that the constructed value captures as much variance as possible of all six individual proxies.

To determine the principal components of the multiple features, our six proxies, we must first standardise the input features. We do so because our six proxies are expressed in different units. For instance, the share of equity issues is expressed as a ratio while the number of IPOs is a nominal number. PCA with features expressed in different units may be misleading as the larger numbers are more likely to explain more of the variance, thereby distorting the analysis. By standardising the features, we express them on a comparable scale, ensuring a representative PCA. To standardise the input features, we utilised the Sklearn StandardScaler, it standardises features by removing the mean and then scaling to unit variance (Pedregosa, et al., 2011). The standardised values, z, of a sample x are calculated as

$$z = \frac{x - u}{s} \tag{9}$$

with *u* as the mean of all samples and *s* as the standard deviation of all samples. The dimension is now reduced by determining a linear combination of all six proxies that explains most of the variance in the proxies (James, Witten, Hastie, & Tibshirani, 2013). This is achieved by performing a spectral decomposition of the covariance matrix to represent it in terms of its eigenvalues and eigenvectors. The eigenvalues indicate which of the eigenvectors helps most to explain variability. The eigenvector corresponding to the highest eigenvalue in magnitude yields the most information about the distribution of the features. If we then multiply this eigenvector with the respective standardised features and take the sum, we get the first principal component, which Baker and Wurgler utilise as an index of investor sentiment.

Recalling the relative timing of the input variables, we determine for each proxy whether its lead or its lag is more suitable for the index. In accordance with Baker and Wurgler, we perform the PCA as described above twice. First, we complete the PCA with 12 features, the six raw proxies and their respective one-month lags. Next, we calculate the correlation of the features with the first principal component, or “first stage index”. For each proxy we then determine whether its lead or its lag has a greater correlation with the first principal component as the correlation indicates how much the respective variable is represented in the component. That is, the correlation with the first-stage index suggests whether the lead or the lag correlates more with the aggregate investor sentiment. We proceed with the feature with the respective greater correlation. With these six raw proxies we perform a second-stage PCA, which yields the final index SENTIMENT (Baker & Wurgler, 2006).

While the index constructed from the six features described in the preceding paragraphs, could be a satisfying approximation to investor sentiment, one might argue that PCA does not differentiate between the sentiment component we aim to investigate and a business cycle component, possibly distorting the picture. That is, the features may fluctuate for rational and irrational reasons. As the component we are interested in is the irrational one, we must isolate the rational fluctuations from each of the proxies. Accordingly, we construct a second index and repeat the steps elaborated on above with features that do not include a business cycle component. To remove the business cycle component, we regress the six raw proxies on macroeconomic indicators (c.f. Section 8.2.1). We then use the resulting residuals as features and follow the above two-stage PCA procedure. Again, we determine whether the lead or the lag is most appropriate to proceed with. Baker and Wurgler argue that these orthogonalized proxies may be a more precise measure of investor sentiment. We define the orthogonalized index as SENTIMENT^.

8.3. Sentiment and Feedback Trading Model

In the previous sections, we discussed the effects of sentiment in financial markets in detail. We identified sentiment and positive feedback as key determinants of financial bubbles. Momentum trading, also referred to as positive feedback trading, and its connection to the development of financial bubbles has been well investigated (Sornette 2009, Antoniou, Doukas & Subrahmanyam, 2010). The following sections elaborate on the methodology behind the feedback trading model developed by Sentana and Wadhwani (1992), and its extension proposed by Chau, Deesomsak and Lau (2011). We are particularly interested in their so-called extended model as it considers the impact of investor sentiment on feedback trading. It is important to note that both, the original model and its extension, were designed for trading in financial asset markets. To apply these models, it was therefore an important step to consider Bitcoin as an asset within the scope of this thesis (c.f. Section 4).

8.3.1 Data Description

To analyse sentiment and feedback trading in Bitcoin markets, we combine the Baker and Wurgler sentiment indices with the feedback trading models elaborated on in the next sections. To do so, we utilise daily Bitcoin prices in U.S. dollar as provided by Yahoo Finance (Verizon Media, 2019). We chose Yahoo Finance as it can reasonably be expected that it provides a comprehensive aggregation of the Bitcoin markets relevant to U.S. investors. Due to the minuscule differences in prices across the Bitcoin trading platforms, analysing each market separately does not provide additional value. We therefore assume that the Bitcoin prices obtained from Yahoo Finance are a fair representation of the Bitcoin markets relevant to us. The Bitcoin price time series was available from the 17th of July 2010 and we obtained prices up to the 31st of December 2018, resulting in 3,090 daily observations (Figure 11 plots Bitcoin prices for the selected time series). For our analysis, we calculate Bitcoin log returns which we interchangeably refer to as returns. Figure 12 depicts the returns calculated for the time analysed.

To match the length of the Bitcoin data set, the daily non-orthogonalized (SENTIMENT) and orthogonalized (SENTIMENT^) sentiment indices are obtained for the same time window, resulting in 3,090 observations. We describe in detail the proxies from which the sentiment index is constructed in Section 8.2.1, and the index conversion from monthly to daily in Section 8.3.3.

Figure 11 – Bitcoin Price

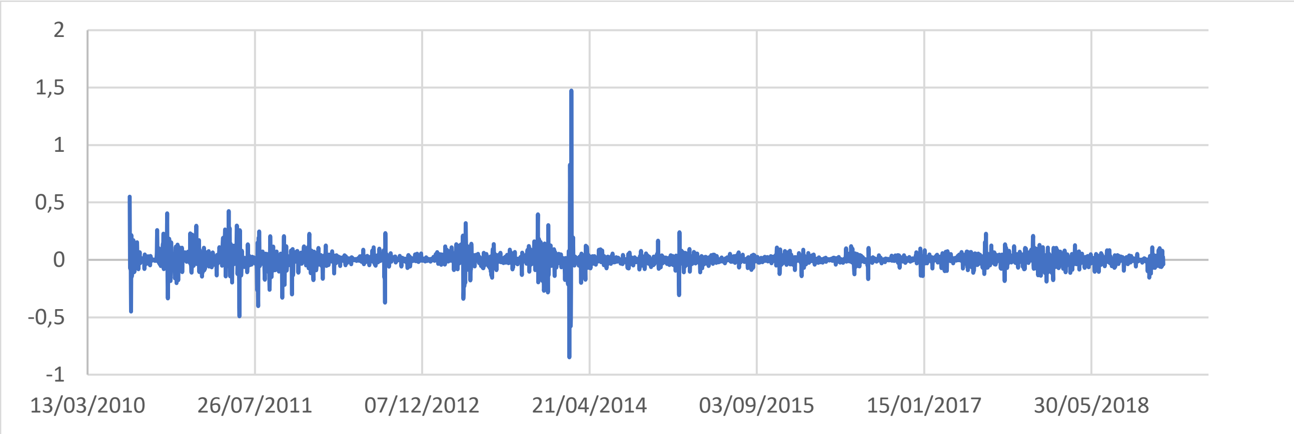

Figure 12 – Bitcoin Daily Return

8.3.2 Feedback Trading Model (Sentana and Wadhwani)

As elaborated on in Section 6, feedback trading plays a significant role in financial market dynamics, with destabilising effects on stock prices (DeLong, Shleifer, Summers & Waldman, 1990). The relation between the autocorrelation patterns of stock returns and the presence of feedback trading received particular attention in feedback trading research, resulting in empirical evidence of significant ties between the two (Koutmos, 1997; LeBaron, 1992; Cutler et al., 1990). Feedback trading models on the nature of this relationship yield several implications. Shiller (1984) and Cutler (1990), for example, find a positive autocorrelation of stock returns when volatility is low. The model proposed by Sentana and Wadhwani (1992) further suggests that the presence of positive feedback trading tends to engender negative first order autocorrelation for high levels of volatility.

Advancing the findings of Cutler et al. (1990), the positive feedback trading model as proposed by Sentana and Wadhwani (1992) considers two types of investors. Rational traders that base their demand on the risk-adjusted expected return and feedback traders that base their demand on previous returns. The model assumes that returns are characterised by a simple autoregressive process "in which the parameter on lagged returns is a function of the conditional variance, i.e. the existence of a relationship between autocorrelation and volatility".

In the model, the rational investors demand S_t shares in period *t* that maximises their expected mean-variance utility:

$$S_t = \frac{[E_{t-1}(R_t) - \omega]}{\theta(\sigma_t^2)} \tag{10}$$

where E_{t-1} is the expected return in period t-1, ω the risk-free return, σ_t^2 the conditional variance in period *t*, and θ the fixed coefficient of risk aversion, with $\theta(\sigma_t^2)$ the required risk premium (Chau et al., 2011). Feedback investors, on the other hand, demand F_t shares based on lagged returns:

$$F_t = \gamma R_{t-1} \tag{11}$$

where R_{t-1} is the return in period t-1, and γ is a dummy variable for the two different types of feedback traders. If $\gamma > 0$, traders exhibit positive feedback trading, buying (selling) when prices rise (fall). Conversely, if $\gamma < 0$, traders exhibit negative feedback trading, buying (selling) when prices fall (rise). When $\gamma = 0$, feedback trading does not exist in the market. As we only consider two types of investors in this model, the amount of the shares in the market equilibrium is equal to the sum of shares held by feedback and rational traders:

$$S_t + F_t = 1 \tag{12}$$

If we assume that all traders in the market are rational, i.e. $S_t = 1$, the market equilibrium as a result of plugging (10) into (12) yields the capital asset pricing model (CAPM):

$$E_{t-1}(R_t) - \omega = \theta(\sigma_t^2) \tag{13}$$

If we instead assume that rational and feedback traders coexist in the market, plugging (10) and (11) into (12) results in

$$E_{t-1}(R_t) - \omega = \theta(\sigma_t^2) - \gamma[\theta(\sigma_t^2)]R_{t-1} \tag{14}$$

We can see that the only difference between the scenario with only rational traders (13) and the one considering both types (14) is the term $\gamma[\theta(\sigma_t^2)]R_{t-1}$. Including lagged returns in the equation indicates that Sentana and Wadhwani assume that the existence of feedback traders may result in the autocorrelation of returns. The extent of that autocorrelation depends on the type of feedback trader dominating the market as indicated by γ, but also on the conditional volatility σ_t^2. As the conditional volatility increases, the relative demand of rational investors decreases (c.f. Equation (10)). Recalling the equilibrium condition (Equation (12)), the relative demand of feedback traders thereby increases, resulting in increased autocorrelation (c.f. Section 6.3.). Interestingly, if positive feedback traders dominate the market ($\gamma > 0$), the autocorrelation of returns is more likely to be negative and vice versa.

If we now assume that expectations are accurate, or rational, implying $R_t = E_{t-1}(R_t) + \epsilon_t$, with ϵ_t as an independently and identically distributed error term, we can plug $E_{t-1}(R_t) = R_t - \epsilon_t$ into Equation (14), resulting in:

$$R_t = \omega + \theta(\sigma_t^2) - \gamma[\theta(\sigma_t^2)]R_{t-1} + \epsilon_t \tag{15}$$

To empirically assess feedback trading in financial markets, Sentana and Wadhwani (1992) modify Equation (15) to:

$$R_t = \omega + \theta(\sigma_t^2) + (\phi_0 + \phi_1\sigma_t^2)R_{t-1} + \epsilon_t \tag{16}$$

where $\phi_1 = -\gamma\theta$. The coefficient ϕ_0 was introduced to the model to account for the autocorrelation related to potential market inefficiencies engendered by the presence of feedback traders (c.f. Section 6.3.). Recalling Equation (11), a positive (negative) ϕ_1 indicates the presence of negative (positive) feedback traders. For indicating the presence of positive feedback traders, either ϕ_1 or ϕ_0 must be negative (Chau et al 2011). In the empirical section and the proceedings of this paper, we refer to Equation (16) as *Baseline Model*, or *Model 1*.

When empirically testing their feedback trading model, Sentana and Wadhwani (1992) utilised a generalised autoregressive conditional heteroscedastic (GARCH) process to model the conditional variance σ_t^2. They simultaneously estimated all the parameters by maximum likelihood and obtained $\hat{\phi}_1 = -0.019$ and $\hat{\phi}_0 = 0.111$. When determining the relation between $\hat{\phi}_1$, $\hat{\phi}_0$, and σ_t^2, Sentana and Wadhwani (1992) found that in high volatility periods, returns are negatively autocorrelated. In low volatility periods, on the other hand, returns tend to be positively autocorrelated. This result implies that positive feedback trading prevails in high volatility periods and negative feedback trading in low volatility periods.

8.3.3 Feedback Trading with Sentiment

Chau et al. (2011) extend the original feedback trading model by permitting sentiment to influence the demand of feedback traders. This is motivated by research suggesting that positive feedback trading is, to some extent, influenced by noise (cf. Sections 2, 3, 4). In this subsection, we introduce the three extended models proposed by Chau et al. (2011).

With respect to the feedback trading model as proposed by Sentana and Wadhwani (1992), the demand of shares of feedback traders solely depends on lagged returns (c.f. Equation (11)). Their demand is thus not affected by varying levels of investors sentiment. In contrast, Chau et al. (2011) believe that the demand of feedback traders should not only take lagged returns into account, but also how optimistic or pessimistic these traders are about the future performance of the stock market. They therefore extend the original Sentana and Wadhwani feedback trading model by modifying the demand function of the feedback traders allowing for the influence of sentiment on feedback traders' demand:

$$F_t = \gamma R_{t-1} + \lambda D_t \tag{17}$$

where D_t is a dummy equal to 0 in pessimistic periods (low sentiment), and equal to 1 in optimistic periods (high sentiment). Similar to Antoniou et al. (2011), this sentiment dummy is determined by calculating a rolling 3-month average of sentiment. Specifically, sentiment is labelled *optimistic* if today's investor sentiment is greater than its lagged 3-month average. In all other cases, sentiment is labelled *pessimistic*. The dummy therefore does not express absolute, but *relative* investor sentiment. To proxy investor sentiment, Chau et al. (2011) employ the Baker and Wurgler sentiment index (c.f. Section 8.2.), with index data retrieved from Wurgler's web page (Wurgler, 2019).

To this end, it is important to recognise that the sentiment can only be determined on a monthly basis as the proxies from which it is constructed are only available on a monthly basis. The Bitcoin returns, however, are obtained daily. Thus, we either need to convert the index to a daily or the returns to monthly format in order to bring returns and sentiment on a common timescale. As the daily volatility of Bitcoin is high, the latter does not make sense as we would lose a lot of information when converting the returns to a monthly format. Since Chau et al. (2011) do not specify how they convert the index from monthly to daily, in the following we present the approaches that we believe to be most reasonable. We consider three feasible alternatives to transform the index to a daily format and choose the one with the best optimisation results (c.f. Section 8.3.4):

(1) The most obvious choice is the repetition of the monthly sentiment dummy, i.e. 1 or 0, for each day of that month. That is, if we determine a dummy of 1 for February, each day of February would have a dummy of 1.

(2) The next choice would be to smooth the monthly transition of these dummies to avoid jumps of sentiment at the end of each month. We therefore consider a 30-day moving average of the sentiment dummies determined in the first alternative.

(3) The last option we consider is first taking the 30-day moving average of the monthly original sentiment indices (SENTIMENT and SENTIMENT^). Thereafter, we calculate the 90-day moving average of the 30-day moving average and compare the two values. If today's sentiment (30-day moving average) is higher than the lagged 90-day moving average, it is considered optimistic (equal to 1), otherwise pessimistic (equal to 0). In other words, analogous to the determination of the monthly dummy, we compare today's sentiment (the 30-day moving average of sentiment) to the lagged 3-month moving average (the 90-day moving average).

It is important to note that sentiment in the context of the feedback trading model always refers to *relative* sentiment. This is because, according to the methodology followed, we compare sentiments states within a given time range and determine the relative sentiment state for such period.

Consistent with Sentana and Wadhwani, Chau et al. (2011) assume rational expectations (i.e. $R_t = E_{t-1}(R_t) + \epsilon_t$). Plugging the original equation for rational investor demand (Equation (10)), and the new demand function of feedback traders (Equation (17)) into the demand equilibrium equation (Equation (12)), we obtain daily returns.

$$R_t = \omega + \theta(\sigma_t^2) - \gamma[\theta(\sigma_t^2)]R_{t-1} - \lambda D_t[\theta(\sigma_t^2)] + \epsilon_t \tag{18}$$

In contrast to the original feedback trading model (Equation (16)), the return at time *t* is now impacted by sentiment, represented by the dummy variable D_t. The intensity of the impact of D_t depends on the sentiment state (if the dummy is equal to zero, we have no impact at all), and on the conditional volatility σ_t^2. Consistent with the original feedback trading model, we again assume $\phi_1 = -\gamma\theta$ and add the constant ϕ_0 to capture autocorrelation:

$$R_t = \omega + \theta(\sigma_t^2) + (\phi_0 + \phi_1\sigma_t^2)R_{t-1} - \lambda D_t[\theta(\sigma_t^2)] + \epsilon_t \tag{19}$$

Chau et al. (2011) further allow the risk-free return ω and the coefficient of risk aversion θ to vary with different states of sentiment D_t and re-parameterise Equation (19):

$$R_t = \omega_H D_t + \omega_L(1 - D_t) + \theta_H D_t \sigma_t^2 + \theta_L(1 - D_t)\sigma_t^2 + (\phi_0 + \phi_1\sigma_t^2)R_{t-1} + \epsilon_t \tag{20}$$

Re-parameterisation in this context refers to a change of variables of a given function *f*, specified by parametric variables $u_1, \dots, u_n$ (Pressley, 2010, p. 13). A reparameterization of, *f*, $(\hat{f})$, over domain U is a replacement of variables $u_i \in U \rightarrow v_i \rightarrow V$ by means of a function ϕ such that

$$\hat{f}(v_i) = f\big(\phi(v_i)\big) \tag{21}$$

and there is an inverse ϕ^{-1} such that

$$\hat{f}\big(\phi^{-1}(u_i)\big) = f(u_i) \tag{22}$$

In other words, a re-parameterisation is nothing more than expressing a given equation with a different set of parameters, but the nature of the equation remains the same. That is, even though we are expressing Equation (20) with a modified set of parameters, it still yields the same information as Equation (19). In the empirical section and the proceedings of this paper, we refer to Equation (20) as *Model 2*. It is the extended Model 1, considering the impact of investor sentiment in an additive manner to the demand function of feedback traders as expressed by Equation (17).

In addition to the additive demand function by feedback traders as expressed by Equation (17), Chau et al. (2011) propose an alternative multiplicative demand function including investor sentiment:

$$F_t = [\gamma D_t + \lambda(1 - D_t)]R_{t-1} \tag{23}$$

with all components identical to the additive demand function. We again assume rational expectations and substitute (10) and (11) into the equilibrium (12):

$$R_t = \omega + \theta(\sigma_t^2) - [\gamma D_t + \lambda(1 - D_t)]\theta(\sigma_t^2)R_{t-1} + \epsilon_t \tag{24}$$

Again, we assume $\phi_1 = -\gamma\theta$, add the constant ϕ_0 to capture autocorrelation, and also allow ϕ_1 and ϕ_0 to vary with different states of sentiment D_t , re-parameterise, and rearrange:

$$R_t = \omega + \theta(\sigma_t^2) + D_t(\phi_{0H} + \phi_{1H}\sigma_t^2)R_{t-1} + (1 - D_t)(\phi_{0L} + \phi_{1L}\sigma_t^2)R_{t-1} + \epsilon_t \tag{25}$$

In the remainder, we refer to Equation (25) as *Model 3*. It is the extended Model 1, considering the impact of investor sentiment by the multiplicative demand function of feedback traders as expressed by Equation (23).

If we now allow all parameters in the conditional mean to vary across investor sentiment states, i.e. combine Model 2 and Model 3, we arrive at an augmented model, which we refer to as *Model 4*:

$$\begin{aligned} R_t = \omega_H D_t + \omega_L(1 - D_t) + \theta_H D_t(\sigma_t^2) + \theta_L(1 - D_t)(\sigma_t^2) + D_t(\phi_{0H} + \phi_{1H}\sigma_t^2)R_{t-1} \\ + (1 - D_t)(\phi_{0L} + \phi_{1L}\sigma_t^2)R_{t-1} + \epsilon_t \end{aligned} \tag{26}$$

8.3.4 Parameter Fitting

In this section we elaborate on the process of fitting the parameters of the four models described in Section 8.3.2 and 8.3.3. In the following we discuss how to model volatility and test for stationarity, followed by a discussion of GARCH models for volatility. Thereafter, we present our routine to compare four GARCH type models and selecting the one for our further analysis. To conclude, we explain the optimisation approach utilised to estimate the parameters.

Volatility Modelling

The first step of estimating the parameters of the feedback trading base model is to determine how to model the volatility of Bitcoin returns. We must first test our time series (the Bitcoin log returns) for stationarity as the GARCH models we intend to employ assume stationarity. Stationarity is a necessary condition as it implies that the properties of the time series (for example mean, variance, and autocorrelation) are time-invariant, allowing us to draw conclusions about how a change in one variable affects another (Box & Jenkins, 1970). Stationarity of the Bitcoin log return time series allows us to model its volatility as an equation with fixed coefficients that are estimated utilising lags of the log returns.

To assess whether our time series is stationary, we utilise the Augmented Dickey Fuller (ADF) test. The null hypothesis of the ADF test is that a unit root persists in the autoregressive model, indicating non-stationarity. By unit root we understand a stochastic trend in a time series that can cause problems in our statistical inference; a well-known example of a unit-root non-stationary time series is a random walk (Wooldridge, 2003). The alternative hypothesis of the ADF test is no unit root which implies stationarity. To execute the ADF test, we first run an ordinary least square regression (Equation (27)) to obtain the estimated standard error, which is then used to generate our ADF t-statistic (Equation (28)).

$$R_t = \vartheta + \Omega \, \mathrm{R}_{t-1} + \epsilon_t \tag{27}$$

$$ADF = \frac{(\bar{\Omega} - 1)}{se(\bar{\Omega})} \tag{28}$$

where R represents Bitcoin log-returns, ϑ is a constant, Ω a parameter and ϵ_t the error term. For the subsequent analysis, the ADF test statistic is compared to the critical values at 1%, 5%, and 10% level. If the test statistic is greater in magnitude than the critical values, we reject the null hypothesis, indicating stationarity.

In research, there is strong consensus that the GARCH model seems to capture volatility in Bitcoin markets best (see, for example, Bouoiyour and Selmi, 2016; Katsiampa, 2017; Bouri, Azzi, Dyhrberg, 2017, Baur et al., 2018), as stock returns are characterised by conditional heteroscedasticity (Chau, Deesomsak, & Lau, 2011). Heteroscedasticity signifies that the standard errors of certain variable, monitored during a specific time series, are not constant over time (Alexander, 2008). In other words, it refers to the case when the variance of a variable is unequal across the values of another variable that predicts it.

Heteroscedasticity is captured by the Autoregressive Conditional Heteroscedasticity (ARCH) model proposed by Engle (1982) that allows for autocorrelation at different levels of time. ARCH models model volatility by adding and weighting past observations, therefore allowing recent volatility to have a higher influence in the short-run. However, this model becomes slightly complicated as it includes several lags, which makes the estimation of the parameter somewhat difficult (Bollerslev, 1986). For this reason, Bollerslev (1986) extended this approach into the General Autoregressive Conditional Heteroscedasticity (GARCH) model which includes declining weights as in the ARCH approach but does not let the weights go to zero. This generated a model that is easier to use and has proven its success in estimating returns volatility (Engle R. , 2001). We therefore only consider GARCH models when determining which model describes the volatility of Bitcoin returns best.

In the following we determine whether the standard GARCH, the GJR-GARCH, the EGARCH, or the TARCH captures the volatility best. We first consider the standard GARCH process, which consist of two equations: A conditional mean equation that determines the behaviour of returns and its error term ε (see Equation (29)), and second the conditional variance equation (see Equation (30) for a representation of the standard GARCH model).

$$y_t = \nu + \kappa y_{t-1} + \epsilon_t \tag{29}$$

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \epsilon_{t-i}^2 + \sum_{i=1}^{p} \beta_i \sigma_{t-i}^2 \tag{30}$$

The conditional mean equation will provide us with an estimation of the errors (or variance) generated in previous periods that is used in the conditional variance equation to forecast variance in future periods. Thereafter, we extend for the different versions of the GARCH model that take into account asymmetries in the behaviour of returns volatility. We chose this approach as it is well-established in the literature that investors tend to react more negatively to price declines (or negative shocks) than positively to price increases (positive shocks). In other words, negative shocks at time *t-1* have a greater influence on the variance at time *t* than positive shocks (Glosten, Jagannathan, & Runkle, 1993). We therefore find that the inclusion of these models could help us to reflect a more realistic representation of the volatility of Bitcoin returns (see Equations (29) and (30)).

Finding the best GARCH model

For each GARCH(p,q) (see Equation (30)) model considered, one must first determine which calibration of p and q, i.e. which respective number of lags, is optimal. To do so, we estimate each combination of p and q from zero to four by maximum likelihood estimation (MLE). That is, we iterate through values of p from one to four and through values of q from zero to four, resulting in 25 possible combinations from (0,0) to (4,4). The likelihood (function) indicates how likely we obtain the observed data under the respective parameter values (Edwards, 1992). MLE is commonly employed for identifying the model parameters that are, given the data, most probable.

We utilise three criteria to decide upon the volatility model that we employ thereafter in our feedback trading and sentiment model. These criteria consider both, the likelihood of the data, and the model complexity. When modelling a finite data set based on maximum likelihood, it is generally likely to increase the likelihood of the model by adding extra parameters, however this may result in overfitting (Burnham & Anderson, 2002). Overfitting in this context refers to the estimation of a model that is only able to represent the underlying 'true' time series, and therefore fails to predict future or additional data in a reliable manner. We therefore determine which GARCH version models the volatility of Bitcoin log-returns best not only by MLE, but also consider the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC) that compare the relative quality of the model fit.

The AIC test, proposed by Akaike in 1974, is designed to select the model whose probability distribution produces the lowest discrepancy with the real distribution (Busemeyer & Diederich, 2014). The obtained value will give us with an estimate of the information that would be lost if we decide to model our data following this approach (Burnham & Anderson, 2002). The better model is therefore the one with the lowest AIC (see Equation (31)).

$$AIC = 2\mathrm{k} - N * \log\left(\frac{\sum \varepsilon^2}{N}\right) \tag{31}$$

where N represents the number of observations and k the number of parameters that we have fitted plus 1.

The BIC is very similar to the AIC. It measures the trade-off between model fit and complexity of the model. Analogous to the AIC, the better model is the one with the lowest BIC (see Equation (32)).

$$BIC = \mathrm{k} * \log(\mathrm{N}) - N * \log\left(\frac{\sum \varepsilon^2}{N}\right) \tag{32}$$

Nonetheless, the model selection criteria have limitations. They can only provide a test of relative quality, i.e. the value can only be compared across different models to test which one is the most accurate. It does not, however, provide information about the quality of the model in an absolute sense (Burnham & Anderson, 2002).

AIC and BIC attempt to reduce the complexity of the model by penalising overly complex models. Both criteria are very similar, however they include different penalties for the number of parameters, 2k for AIC, and ln(n)*k for BIC. Note that BIC penalty increases both with the addition of parameters and observations. As the BIC penalises overfitting more severely than the AIC, we conclude that the models selected by the AIC lean towards overfitting, while the ones selected by the BIC lean towards underfitting (Box & Jenkins, 1970). As parsimonious (simple) models generate better forecasts than over-parameterised ones, we put more weight on the BIC as a selection criterion when in doubt. We then compare the resulting best p and q calibration for each GARCH model and choose the model with the overall smallest AIC and BIC values.

Parameter Fitting

After determining the most suitable GARCH model for Bitcoin returns, we calibrate the parameters for Model 1, Model 2, Model 3, and Model 4. The parameter estimation for the volatility and the feedback trading model is conducted simultaneously by MLE with the respective chosen optimal GARCH model. The parameter fitting procedure is repeated 24 times: each of the four models analysed is fitted for both, the orthogonalized and the non-orthogonalized sentiment index, as well as for each of the three sentiment index conversion options. To test for serial autocorrelation of the residuals, we employ the Box-Pierce statistic, a portmanteau test, with 12 lags (Box & Pierce, 1970). The test can be used to investigate the adequacy of the mean equation (Tsay, 2010). The null hypothesis is that the residuals are white noise (serially uncorrelated). If the p-values are above 5% we are not able to reject the null hypothesis which suggests that the model captures most of the information of the time series it represents.

9. Empirical Results

In this chapter, we present the empirical results. In Section 9.1, we introduce the sentiment indices followed by a short description of several critical economic events that the sentiment indices capture. Detailed information on the six proxies is presented alongside. The results on the feedback trading models are presented in Section 9.2, together with a short comment on the main findings.

9.1. Empirical Results (Sentiment Index)

In this section we present the results obtained in the construction of both, the orthogonalized sentiment index (SENTIMENT^) and the non-orthogonalized one (SENTIMENT). Highlights and indicators are presented in parallel for both sentiment indices. As stated in Section 8.2. we utilise the standardized raw data for the non-orthogonalized index and the standardized residuals obtained from the regression of each of the proxies to six macroeconomic indicators for the orthogonalized index.

As established in Section 8.2.2, we first conduct the PCA with 12 features, the lead and one lag of the six proxies, resulting in the first principal component, or “first stage index”. To determine whether the lead or the lag is more appropriate, we calculate each of the variable’s correlation with the first stage index. The choice between lead and lag depends on the magnitude of the correlation, i.e. we pick those proxies that exhibit a higher correlation in absolute terms. Table 1 displays the correlations found for both indices with the selected variables highlighted in bold.

SENTIMENT						
	ripo	*nipo*	*s*	*cefd*	*turn*	*pdnd*
Lead	0.2295	0.1789	**0.7492**	**0.8152**	0.3699	-0.377
Lagged	**0.3455**	**0.2956**	0.7431	0.7805	**0.3906**	**-0.4222**
SENTIMENT^						
	ripo	*nipo*	*s*	*cefd*	*turn*	*pdnd*
Lead	0.0176	0.3521	**0.7949**	**0.6372**	**0.1696**	-0.1441
Lagged	**0.0779**	**0.4421**	0.7807	0.6298	0.1032	**-0.1613**

y

Table 1 – Correlation of variables with first stage indices

Overall, the proxies display strong correlations with the first stage index. Once the six definitive variables have been selected, we repeat the process again to obtain the final first principal component with the proxy values that compose the sentiment indices. We construct the sentiment index as a linear combination of the six variables by using the eigenvector linked to the highest eigenvalue (see appendix A.1) as the corresponding weights. This leads to Equations (33) and (34).

$$SENTIMENT = 0.3860\, ripo_{t-1} + 0.3140\, nipo_{t-1} - 0.4820\, S_t + 0.5291\, cefd_t + 0.3327\, turn_{t-1} - 0.3594\, pdnd_{t-1} \tag{33}$$

$$SENTIMENT^{\wedge} = 0.1963\, ripo_{t-1} + 0.5105\, nipo_{t-1} + 0.5734\, S_t + 0.5397\, cefd_t + 0.1795\, turn_t - 0.2201\, pdnd_{t-1} \tag{34}$$

The correlations of SENTIMENT and SENTIMENT^ with their respective first stage indices are 0.9479 and 0.9104 respectively. The fact that correlations are close to 1 implies that we do not lose much information by dropping either the lead or the lagged variable for each of the proxies. Furthermore, the explained variance ratio of SENTIMENT equals 0.3137 and the explained variance ratio of SENTIMENT^ equals 0.2463. That SENTIMENT^ explains less variance is not surprising as the orthogonalization removed structure from the residuals. Hence, explaining the variance of all the variables with one component becomes more difficult.

Overall, the resulting signs with which the respective proxies enter the SENTIMENT^ equation match our expectations with the exception of *cefd* for which an inverse relationship to sentiment was expected. Nonetheless, we encounter the same directions for SENTIMENT with one exception as the value of *s* turned from positive to negative when business cycle components are not removed. In this regard, we find that the direction of the correlation between the proxy *s* and the sentiment indices radically changes when regressed against fundamentals (see Table 2). This result, together with the fact that we do not find strong statistical significance between variable *s* and SENTIMENT^, leads to the conclusion that the macroeconomic factors in proxy *s* had a strong impact in the construction of SENTIMENT. In contrast, the negative impact of the dividend premium (*pdnd*) proxy is detected for both indices as expected. The resulting indices are depicted in Figures 13 and 14.

The correlation between both indices is 0.61. This implies that both indices tend to generally move in parallel but are not perfectly synchronized. We attribute the difference to the influence of the business cycle components. Furthermore, we find an overall stronger correlation between the variables and the orthogonalized index than with the non-orthogonalized. If the raw variables were driven by common macroeconomic conditions (that we failed to remove through orthogonalization) instead of common investor sentiment, one would expect that correlation between the proxies and the index would decrease after orthogonalization.

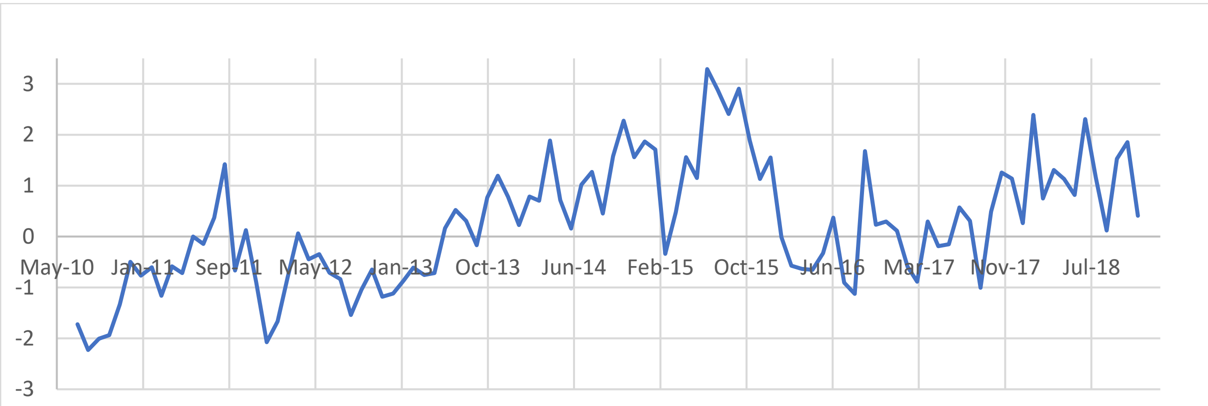

Figure 13 - SENTIMENT

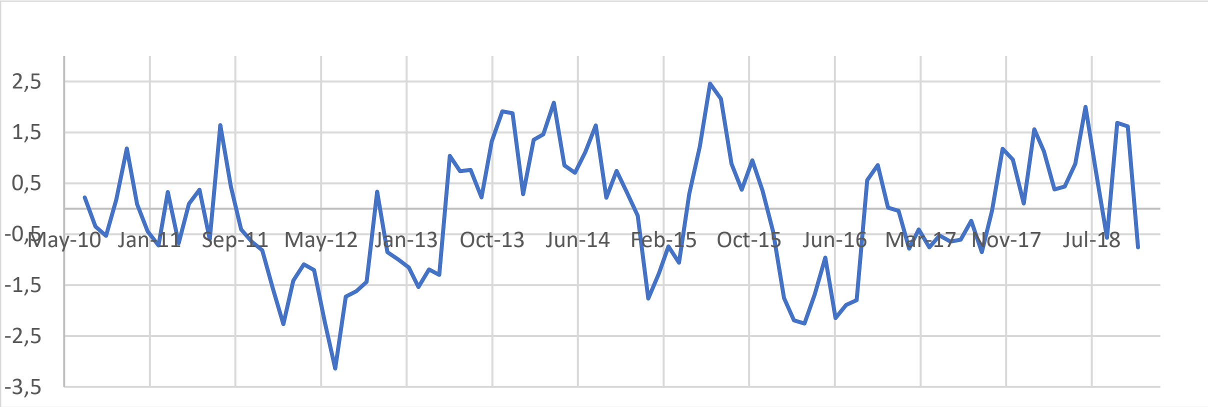

*Figure 14 – SENTIMENT^*

					Correlation with indices		Correlation Matrix					
	Raw Data											
	Mean	SD	Min	Max	SENTIMENT	SENTIMENT^	RIPO	NIPO	s	cefd	turn	pdnd
RIPO(t-1)	14.48	10.52	-6.00	46.00	0.4749***	0.3071***	-0.04					
NIPO(t-1)	16.86	8.30	0.00	37.00	0.3806***	0.6627***	0.11	0.39				
s	0.12	0.03	0.00	0.24	-0.4572***	0.05	-0.02	0.45	1.00			
cefd	4.57	2.73	-0.41	9.85	0.7725***	0.4999***	-0.03	0.02	-0.47	1.00		
turn	-0.02	0.12	-0.28	0.47	0.4925***	0.09	-0.08	-0.12	-0.12	0.30	0.25	
pdnd(t-1)	-0.35	0.08	-0.54	-0.16	-0.4185***	-0.3220***	-0.05	0.07	-0.23	-0.14	-0.15	0.85
	Controlling for macroeconomic variables											
RIPO(t-1)	0.00	10.10	-17.69	33.54	0.3924***	0.2593***	-0.12					
NIPO(t-1)	0.00	7.54	-14.82	17.04	0.2811***	0.6387***	0.04	0.39				
s	0.00	0.02	-14.82	0.03	0.2857***	0.6914***	0.12	0.45	0.03			
cefd	0.00	1.46	-3.03	3.07	0.4766***	0.6713***	0.04	0.02	0.01	0.62		
turn	0.00	0.11	-0.23	0.51	0.1796*	0.2142**	0.08	-0.12	-0.14	0.17	0.94	
pdnd(t-1)	0.00	0.07	-0.22	0.22	-0.3463***	-0.3225***	0.02	0.07	-0.06	-0.10	-0.11	0.68

Table 2 - Summary Statistics (SENTIMENT and SENTIMENT^)

Figure 15 presents a comparation of SENTIMENT^ and the evolution of the NYSE Composite index. In addition to the graph, we include comments on the most notable shifts in sentiment to assign ups and downs to fundamental events occurred, seeking to align our results with price fluctuations (Figure 15). The most relevant economic events we identify are the following.

- 2011. Bull market during the first half of the year that would lead up to the black Monday on the 5th of August after the credit rating downgrading of the US sovereign debt (Bowley, 2011). SENTIMENT^ indicates a rough decline in sentiment starting from August onwards.

- 2012. Long-run bull market since the black Monday in 2011 that ended in March with a maximum, preceding a rough downturn in May driven by concerns of another global slowdown (Guardian News & Media Limited, 2012). SENTIMENT^ shows an upwards direction that changes after March, subsequently experiencing a large decline.
- September 2015. Chinese crisis (Hsu, 2016) that brought major drops in U.S. financial markets captured by the index.
- 2016. January initiates a period of price drops and low sentiment as a consequence of oil prices hitting a 12-year low (Egan, 2016), followed by the Brexit vote announcement in February (Srivastava, 2017).
- 2018. Historical peak reached in January characterized by an upsurge of sentiment, followed by a small subsequent correction in both, sentiment and prices.
- End of 2018. General political instability causes major drops in U.S. largest indices (Barbieri & Goldman, 2018).

We note that the sentiment index is used as a relative measure of sentiment. As explained in Section 8.3.3, we differentiate between high (optimistic) and low (pessimistic) sentiment and determined that a period is optimistic if the current level of sentiment is higher than the lagged 3-months average. In this regard, we understand that even if a period has a positive value in the sentiment index, it could be categorised as pessimism if it is experiencing a downwards trend. Note that the financial events depicted in Figure 15 have been selected taking the relativeness of sentiment into consideration. When the sentiment index is plotted together with the NYSE composite index (Figure 15) price evolution, this argument is easier to support, especially in certain periods that are highlighted in the graph below.

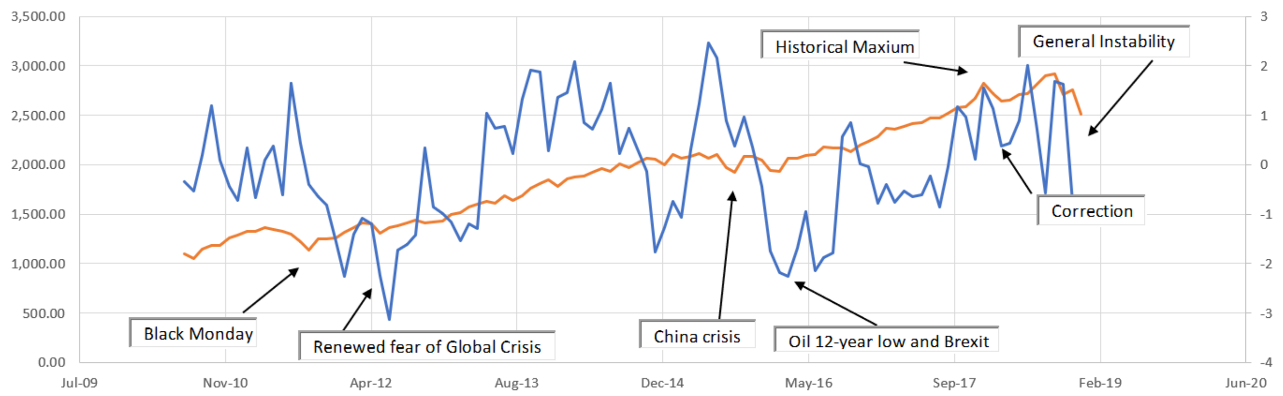

Figure 15 – SENTIMENT^ vs NYSE Composite Index

Even though our measure of sentiment could be a potential indicator of the level of sentiment in the market, it is relevant to point out that it is mainly noise investors who are directly influenced by sentiment. Therefore, the influence of sentiment on the level of prices of indices such as the NYSE might be more limited as the presence of institutional investors is higher. Arbitrage possibilities that are offered in the market are wider, as well as the companies included on the indices tend to be less speculative.

Baker and Wurgler sentiment indices' best proof of success in capturing sentiment is the lining up of the index with major bubbles and crashes. As our time period does not include such events, one of the weaknesses of our thesis is data limitation. No major shocks or bubbles are detected in the NYSE during the selected time series which is characterised for an overall bullish market and economic growth right after the big shock of 2008. although we have attempted to line up our findings with major events in financial markets, we find discrepancies that may add noise to our analysis.

9.2. Empirical Results (Feedback Trading Models)

As laid out in Section 8.3, we first test the time series of Bitcoin returns for stationarity before modelling its volatility. To do so, we run an ADF test and conclude that the Bitcoin returns are stationary, with an ADF statistic of -22.022886 and a p-value < 0.01. As the test statistic is larger in magnitude than the critical values at 1%, 5%, and 10% level (-3.432, -2.862, and -2.567 respectively), the null of non-stationarity is rejected at a 1% confidence level.

Following Chau et al. (2011), we determine the GARCH model specification that best captures the volatility of the Bitcoin returns. As described in Section 8.3.4, we first determine the optimal number of lags, p and q, for each of the four different types of GARCH models. Overall, we notice that the AIC, BIC, and MLE values improve considerably from p=0 and q=0 to p=1 and q=1 across all GARCH specifications. Thereafter, however, the model performance only seems to improve marginally. We further noticed that EGARCH seems to perform best. It is, however, only outperforming the other three GARCH types by a small margin. This result is particularly interesting as it is consistent with the inconclusive results in the literature on modelling volatility on cryptocurrency markets (see, for example, Dyhrberg, 2016; Katsiampa, 2017, Baur et al., 2018). As the market is still evolving and not matured yet, one explanation for the inconsistency in optimal GARCH models could be changing volatility dynamics. Depending on the choice of the time period, the optimal model capturing volatility possibly changes across chosen time periods.

The detailed result tables of the AIC, BIC, and MLE for each of the GARCH models considered can be found in the appendix (A.2). As the relative quality of the models only improves marginally and as we generally prefer parsimonious models over over-parameterised ones, we proceed with the EGARCH(1,1) when fitting the parameters of the feedback trading models. Table 3 shows the AIC, BIC, and MLE of GARCH(1,1), GJR-GARCH(1,1), EGARCH(1,1), and TARCH(1,1):

	GARCH (1,1)	GJR-GARCH (1,1)	EGARCH (1,1)	TARCH (1,1)
AIC	6081	6082	6028	6097
BIC	6105	6113	6058	6127
MLE	-3036	-3036	-3009	-3043

Table 3 - – Comparison of GARCH Models

The EGARCH model has interesting features. As the TARCH model, it allows for an asymmetric effect of news. This is a particularly useful feature as ‘bad’ news tend to have a greater effect on volatility than ‘good’ news (Enders, 2015) which aligns with the role of media in Bitcoin markets established in Section 7.2. Furthermore, when stock returns increase, volatility tends to decline. That is, current returns and future volatility are negatively correlated. According to Enders (Enders, 2015), the reason for this phenomenon is that a negative stock price shock decreases the financial worth of a firm’s equity compared to its debt, thereby increasing the debt-to-equity ratio. This increased leverage in turn increases the risk associated with that firm’s stock which is why this phenomenon is often referred to as the leverage effect. The EGARCH, proposed by Nelson (1991), models the log-linear conditional variance:

$$\ln \sigma_t^2 = \alpha_0 + \sum_{i=1}^{P} \alpha_i \left(\left| \frac{\epsilon_{t-i}}{\sigma_{t-i}} \right| - \sqrt{\frac{2}{\pi}} \right) + \sum_{j=1}^{o} \delta_j \frac{\epsilon_{t-j}}{\sigma_{t-j}} + \sum_{k=1}^{q} \beta_k \ln \sigma_{t-k}^2 \tag{35}$$

For modelling the volatility of the Bitcoin log returns we utilise an EGARCH (1,1), with a fixed order o=1. The standardisation of ϵ_{t-1} (its division by σ_{t-1}) permits a more natural understanding of the magnitude and perseverance of shocks (Nelson, 1991) by making sense of the value of δ (see below). Figure 16 below shows the conditional volatility over time.

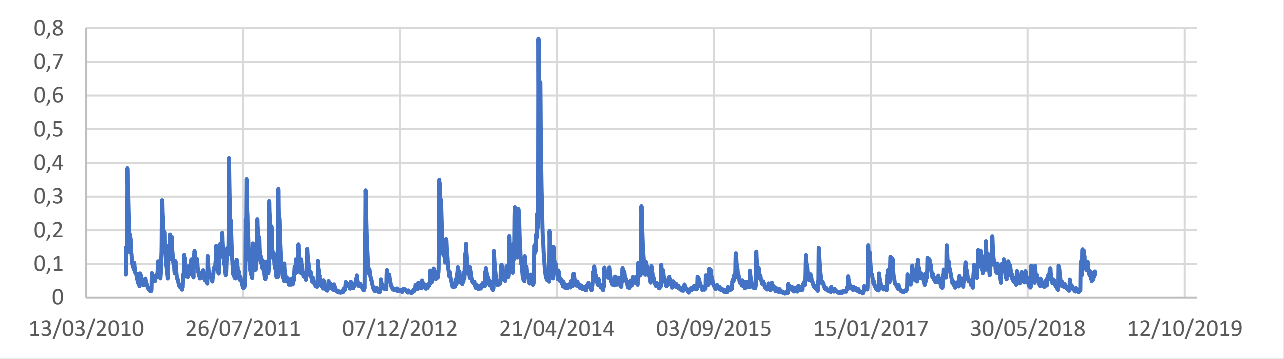

Figure 16 - Bitcoin Daily Returns Volatility

After determining the most suitable GARCH model for Bitcoin returns, we calibrate the parameters for Model 1, Model 2, Model 2, and Model 4. As explained in detail in Section 8.3.4, the parameters are estimated simultaneously by substituting the EGARCH equation into the respective model and then minimising ϵ_t.

To simultaneously estimate the parameters, we tested multiple optimisation algorithms, for example Nelder-Mead, Sequential Least Squares Programming, conjugate gradient, and Newton-CG. We found that the gradient-based methods did not converge to a solution. This problem is consistent with Chau et al. (2011), who encountered convergence issues as well. To solve this problem, we optimised the minimisation problems in two rounds: In the first round we utilised the Broyden-Fletcher-Goldfarb-Shanno (BFGS) algorithm (Nocedal & Wright, 2006, p. 136). We chose that method as a starting point as it is renowned for its good performance for non-smooth optimisations such as ours. The second rounds of optimisation then started from the parameter calibration at which the first round stopped. We chose this approach as the first round of optimisation routinely did not terminate successfully. The second round was optimised with the Nelder-Mead method (Nelder & Mead, 1965). It proved to be the most stable optimisation method, with consistent results, and is one of the most popular algorithms for multidimensional unconstrained optimisation as it is relatively simple, robust, and easy to use. As it does not expect derivative information, it is convenient for optimisations with complex functions (bquanttrading, 2016).

Considering that the simultaneous optimisation involves the exponential GARCH, it is no surprise that we require such a robust algorithm as the exponential component can easily 'explode' in value, complicating the convergence to a stable solution. It is important to bear in mind, however, that it is possible that there are multiple (local) minima to our minimisation problem. As the algorithm will only find the next minimum from the starting values, we choose starting values that are close to the values that we would expect and start from different starting values around the expected values to ensure that the algorithm always iterates towards the same minimum.

As described in Section 8.3.3, we consider three different approaches to convert the Baker and Wurgler sentiment index from monthly to daily. All three options were tested in the parameter fitting procedure. We further conduct the testing and fitting procedure for both, the orthogonalized and the non-orthogonalized, resulting in 24 optimisation attempts (four models, three index conversion options, two versions of the raw sentiment index). Interestingly, only for the first conversion option convergence can be reliably achieved. We therefore proceed with utilising the monthly sentiment value for each day of that month.

In the following, we present the results for Models 1,2,3, and 4 obtained in the parameter fitting procedure described above (Tables 4 and 5). A summary of the optimisation that resulted in a minimum for SENTIMENT^ is stated in Table 5, a summary of the results for SENTIMENT is stated in Table 4. To test for serial autocorrelation in the residuals of the models, we employed Box-Pierce tests. The test indicates remaining correlation in residuals. This result suggests that further extensions towards more complex models are needed and highlights the difficulty of modelling daily Bitcoin returns. Nonetheless, we conclude that the model fit is acceptable for this analysis with a relatively small Mean Square Errors (MSE) (Table 4).

Let's recall the connotation of the parameters: ω is the risk-free return, θ is the fixed coefficient of risk aversion, ϕ_0 is the constant component of autocorrelation, and ϕ_1 indicates the relationship between autocorrelation of returns and volatility as well as determines the presence of each type of feedback trading ($\phi_1 < 0$ suggests that positive feedback trading is present in our market, while $\phi_1 > 0$ suggests that negative feedback trading is present).

	Model 1	Model 2	Model 3	Model 4
Mean Equation				
ω	-0.0010		-0.0020	
ω_H		0.0000		-0.0010
ω_L		-0.0020		-0.0010
θ	0.5270		0.5030	
θ_H		0.5170		0.4470
θ_L		0.4350		0.0990
ϕ_0	0.1000	0.0960		
ϕ_{0H}			0.1360	0.1260
ϕ_{0L}			0.0500	0.0470
ϕ_1	-0.5230	-0.5080		
ϕ_{1H}			-0.5610	-0.4840
ϕ_{1L}			-2.0960	-2.6320
Variance Equation				
α_0	-0.0530	-0.0450	-0.0440	-0.0180
α_1	0.4760	0.4810	0.4710	0.5040
β	0.9740	0.9790	0.9690	0.9700
δ	-0.2440	-0.2410	-0.2570	-0.2710
MSE	0.0044	0.0044	0.0044	0.0044

Table 4 - Parameter Calibration (SENTIMENT)

Let us first consider the four models with non-orthogonalized sentiment. The calibration of the coefficients of the variance equations (α_0, α_1, β, δ) seems within a reasonable range. The negative parameter δ suggests that negative shocks are apt to have a greater impact on volatility thus indicating the presence of asymmetric behaviour (Tsay, 2010), which is the result we expected. Also, we expect positive values for strictly positive values for α_1 and β. The larger value of β indicates that the conditional variance exhibits more autoregressive persistence. With an α_1 considerably different from 0 we assume that the conditional variance is sensitive to new information (Enders, 2015). We further notice that the estimation of the coefficients of the variance equation, as well as the MSE, is strikingly consistent in magnitude and sign across models, suggesting a certain extent of robustness of the results across the four types of models.

It is no surprise that the risk-free return ω is negative across all models, though the risk-free return in high sentiment periods for Model 2 is almost zero. The period under consideration is characterised by historically low interest rates, with an Effective Federal Funds Rate close to zero for approximately two-thirds of that period (Federal Reserve Bank of St. Louis, 2019). Consistent with Sentana and Wadhwani (Sentana & Wadhwani, 1992), we find positive ϕ_0 and negative ϕ_1 across all models. As mentioned in Section 8.3.2, the negative ϕ_1 indicates the presence of positive feedback trading. The sign switch from the positive ϕ_0 to the negative ϕ_1 is interesting; taken together with the conditional variance, this result suggests that returns are positively correlated in periods of low volatility, but negatively autocorrelated in periods of high volatility (Chau, Deesomsak, & Lau, 2011). We find a negative relationship between the autocorrelation of stock returns and volatility across different sentiment states which is consistent with the notion of the existence of positive feedback traders in both scenarios. In addition, ϕ_1 is more negative in periods of low sentiment in both, Model 3 and Model 4, implying that positive feedback trading is more dominant during pessimistic periods. This notion is, however, inconsistent with theory that suggests that markets tend to be more irrational in periods of high sentiment as noise investors dominate the market (Yu & Yuan, 2011).

	Model 1	Model 2	Model 3	Model 4
Mean Equation				
ω	-0.0010		-0.0010	
ω_H		0.0050		0.0060
ω_L		-0.0020		-0.0050
θ	0.5270		0.4160	
θ_H		-0.0740		-0.0330
θ_L		0.5710		0.7490
ϕ_0	0.1000	0.1160		
ϕ_{0H}			0.1060	0.0980
ϕ_{0L}			0.1060	0.1440
ϕ_1	-0.5230	-0.5280		
ϕ_{1H}			-0.6310	-0.5170
ϕ_{1L}			-0.4210	-0.7220
Variance Equation				
α_0	-0.0530	0.0260	0.0040	0.0110
α_1	0.4760	0.4130	0.5360	0.3560
β	0.9740	1.0030	0.9750	1.0070
δ	-0.2440	-0.2980	-0.2680	-0.2550
MSE	0.0044	0.0043	0.0044	0.0043

Table 5 - Parameter Calibration (SENTIMENT^)

Let us now consider the four models with orthogonalized sentiment. Again, the estimated coefficients of the variance equation seem reasonable. As in the scenario with non-orthogonalized sentiment, δ is negative across all models, indicating a larger impact of negative shocks on conditional volatility. The relatively large value of β again indicates that the conditional variance displays autoregressive persistence, and the $\alpha_1$considerably different from 0 indicates sensitivity to new information. Again, the estimated coefficients are remarkably consistent in magnitude and sign across models (with the exception of the constant α_0 in Model 1), the minimisations were successfully terminated, and the MSE are low and comparable to the scenario with non-orthogonalized sentiment, indicating that the minimisation procedure is fairly stable.

It is an appealing result that the calibration of ω is consistent across the models. Nonetheless, we see, contrary to the scenario with the non-orthogonalized sentiment, that the risk-free return ω is positive in periods of high sentiment (see Model 2 and Model 4). Again, it is no surprise that the risk-free return ω is negative for Model 1 and Model 3 as overall interest rate levels were generally low in the period we considered. The higher risk-free return in periods of high sentiment is consistent with the results obtained by Chau et al. (2011).

As in the case with non-orthogonalized sentiment, ϕ_0 is positive across models and sentiment, and ϕ_1 is negative across models and sentiment states, therefore allowing again the existence of positive feedback trading in both sentiment states. Once more we see the sign reversal from ϕ_0 to ϕ_1, confirming the above results. Nonetheless, the results obtained on the greater magnitude of ϕ_1 in low sentiment periods are ambiguous. While Model 4 confirms the above results, Model 3 shows a reverse effect, with ϕ_1 being more negative in high sentiment periods. This result might be caused by the difficulty of the minimisation process (c.f. Section 10.4); future research should investigate this paradoxical result more closely. Overall, we conclude that the existence of positive feedback trading in Bitcoin markets is highly probable. This finding is consistent with the literature (see for example (Kurov, 2008)) that documents that the level of positive feedback trading increases when investors are optimistic.

Chau et al. (2011) find that Model 3 shows a higher degree of accuracy in capturing the variability of feedback trading across the different states of investor sentiment (under the orthogonalized sentiment index). Following their findings, our estimation of Model 3 reflects an approach that is consistent with the literature. This is supported by the existence of an inverse relationship between volatility and returns autocorrelation as stated above, and also by a lower level of stock autocorrelation when sentiment levels are low.

To conclude the presentation of results, we plot the general level of the serial correlation found in the investigated time series below (Figure 17). The implied autocorrelation is extracted from the expression in the Model 1 ($\phi_0 + \phi_1\sigma_t^2$). Overall, we find positive autocorrelation of returns. This result is not surprising as Bitcoin price experienced positive returns for most of the time. Again, the inclusion of ϕ_0 and its positive value allows for the existence of a shift in stock serial correlation that is inversely related to volatility. We find, therefore, that for abnormally high levels of volatility, positive feedback traders have a higher influence in the market. This is further proven by the existence of negative serial correlation in the period of 2014 when the price of Bitcoin experienced serious reversals. In the next Section, we further comment on and make sense of the results presented in this section.

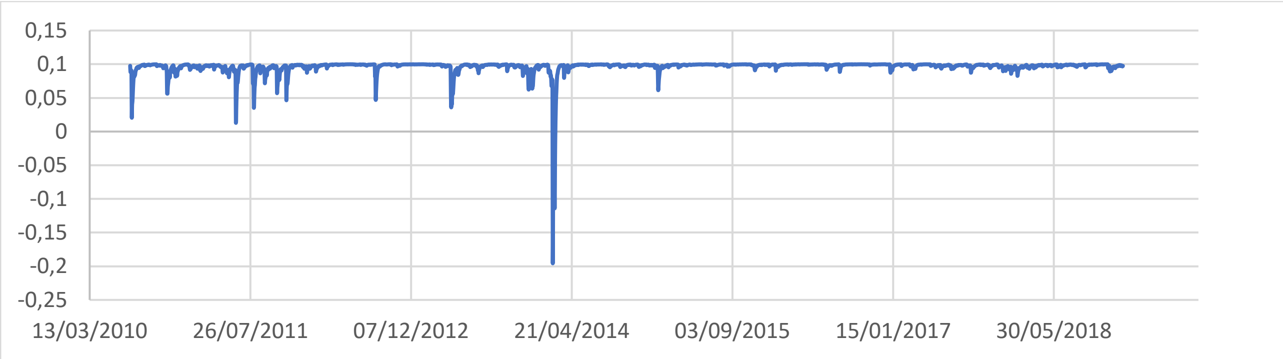

Figure 17 - Implied Autocorrelation of Returns

10. Discussion

The quantification of investor sentiment and feedback trading in financial markets is a controversial topic. Sentiment and feedback trading are particularly relevant in Bitcoin markets as they are seemingly more susceptible to disruptive events than established markets. Yet, the knowledge about the extent of feedback trading in Bitcoin markets and how it is affected by investor sentiment prevailed rather limited. This master's thesis contributes to the scientific endeavour by combining established research in the fields of investor sentiment and feedback trading, and then applying these theories to Bitcoin markets. As mentioned in the introduction, cryptocurrency markets grow while remaining largely unregulated, creating fertile ground for the creation of speculative bubbles. Considering the sheer amount of funds invested in cryptocurrency markets and the potential domino effect if a bubble bursts, the understanding of the antecedents of such bubbles has become more and more important.

We acknowledge the previous work that allowed us to further the understanding of investor behaviour in Bitcoin markets. The sentiment index developed by Baker and Wurgler (2006, 2007) enabled us to calculate a proxy to measure investor sentiment for the period we were interested in. The model proposed by Sentana and Wadwhani (1992), and the extensions presented by Chau et al. (2011), provide us with the means to study the feedback trading dynamics in Bitcoin markets and their variability to different sentiment states.

In the following sections, we interpret the results presented in Section 9 and discuss their implications. We then address the research questions presented in Section 2. Thereafter we discuss the limitations of this work and how future research might further the understanding of cryptocurrency markets.

10.1. Serial Correlation of Returns in Bitcoin Markets

In this section we make sense of the results for Model 1 presented in Section 9.2 and contextualise them with respect to applicability and theoretical implications. As established in Section 6 and Section 8, we would expect to find serial correlation in price returns if a certain group of traders follows feedback trading strategies, i.e. this class of traders bases investment decisions on past price changes. In addition, as volatility rises, rational traders will step out of the market and allow noise traders to have a higher influence on prices, further impacting the extent and direction of serial correlation (Sentana & Wadhwani, 1992).

The aim of our thesis was not only to address feedback trading in Bitcoin markets but to also study the link between volatility and the autocorrelation of returns utilising daily Bitcoin prices under the model (Model 1) proposed by Sentana and Wadhwani (1992). Our results, as indicated by ϕ_0 and ϕ_1, show that Bitcoin returns exhibit positive autocorrelation that declines with volatility. This is indicated by the implied autocorrelation function ($\phi_0 + \phi_1\sigma_t^2$) in which the negative sign of ϕ_1 allows for this inverse relationship. The positive sign of ϕ_0 allows returns to display positive autocorrelation when volatility levels are relatively low, and negative correlation takes over for high levels of volatility. This finding is important for two reasons. First, we prove that previous research exerted in financial markets in which volatility is inversely related with the autocorrelation of returns can be applied to Bitcoin markets. We have shown that as volatility rises, the level of positive feedback trading tends to be more prominent in the market. Second, the finding that Bitcoin returns seem to behave closely related to stocks provides further evidence against the consideration of Bitcoin as a currency. Our results closely resemble the ones obtained by Sentana and Wadhwani (1992) as well as Chau et al. (2011), implying that models that were designed for 'classic' markets can indeed be reasonably applied to Bitcoin markets.

The finding that the level of positive feedback trading increases with volatility is important (c.f. Section 9.2). We do not find a predominant level of (implied) negative autocorrelation in the market for our given time series. One exception are the price increases and subsequent corrections occurred in 2014 where volatility and return levels grew to extremely abnormal figures (Figure 12 and 16). The fact that positive feedback takes over during the 2014 price increases may give us an intuition of the degree of speculation that occurred in the market as more feedback traders were attracted to the market by its potential to realise positive returns.

It is not surprising, however, that Bitcoin returns have mainly experienced positive autocorrelation across the time series we consider. Given the estimated parameters, the level of conditional volatility required to turn implied autocorrelation ($\phi_0 + \phi_1\sigma_t^2$) negative (as we generally find a large ϕ_0) suggests that the presence of negative feedback trading has mainly dominated the market, or at least that traders in general were able to lock in a profit. This may not be surprising as Bitcoin prices have experienced atypical positive daily returns evolving from a market value of 8 cents to almost 20,000 USD. Moreover, it does not rule out the possibility of speculative forces dominating the market but indicates that negative feedback trading, also referred to as rational speculation, prevail. While this result may seem counter-intuitive at first, particularly considering the extensive research and media coverage on speculative bubbles in Bitcoin markets, one must bear in mind that we consider a period of approximately eight years in our analysis. That is, while the implied conditional autocorrelation indicates that negative feedback trading dominates over *the majority* of time, it is perfectly possible that positive feedback trading dominates in recent years.

In turn, the time horizon covered might also constitute a weakness of our analysis. The model is not able to capture negative autocorrelation of returns in the disruptive peak experience during 2017 and 2018 and its subsequent correction, where we would have expected that positive feedback traders should have a higher presence in this upsurge of prices. Bitcoin is notorious for its intraday volatility levels and price fluctuations (Baur, Hong, & Lee, 2018). Our parameters, however, indicate a higher influence of positive serial autocorrelation of returns which suggests that trends tend to persist longer. We suppose that this somewhat surprising result is rooted in the choice of period that we consider in the parameter fitting process. As we do not only consider the period with extreme growth in 2017 and 2018, but instead a range from July 2010 to December 2018, it is only to be expected that the parameters are not exactly representative of this comparably short period.

The results might further be biased by the initial positive growth of prices that predominate during the whole time series, which intuitively may yield positive autocorrelation. In favour of this argument, the model captures negative autocorrelation of returns in February 2014 where prices experienced ups and downs of about 100% of its value in just a range of eight days and a value range of 111 USD to 596 USD. Nevertheless, even though Bitcoin prices suffered rough fluctuations during the end of 2017 and 2018, daily price transitions are smoother which complicates the ability of the model to capture negative serial correlation. Furthermore, it is important to bear in mind that we fit the model on *log returns* and not on prices, which are equivalent to the percentage change in price. As the price level of Bitcoin increased considerably over the years, the same absolute change in price results in a lower log return when the general price level is high. For example, suppose an absolute price change of 10 USD. If the initial price is 20 USD, then a price change of 10 USD to 30 USD results in a log return of 41%, while a price change from 220 USD to 230 USD is equivalent to a log return of 4%. It is therefore not surprising that the inclusion of the *relatively* large returns in the middle of 2010 has a greater impact on implied conditional autocorrelation than the *relatively* low returns in 2017.

Our conditional volatility function may therefore not be able to capture the real level of volatility exhibited in recent years in Bitcoin markets. While the price development may seem explosive, the plotted log returns are less impressive (Figures 11 and 12). Another explanation might be that we do not consider the appropriate 'time unit' of Bitcoin to capture negative correlation of returns. That is, as Bitcoin displays high levels of intra-day volatility, choosing hourly instead of daily returns could have led to different results. As Sentana and Wadhwani include hourly returns in their research, the inclusion of hourly observations may help to explain Bitcoin volatility closer and disclose patterns that we were not able to observe. This becomes more evident when considering that Bitcoin markets are not confined by market opening hours but available all day.

Indeed, other reasons may be involved when making sense of the existing positive autocorrelation of bitcoin returns. Factors such as the level of maturity of Bitcoin markets, the technological innovation that surrounds it or its complexity at both technological and valuation level may all have an impact on the price evolution that we are unable to see at first sight and underlie different types of speculative forces.

10.2. Influence of Sentiment on the Serial Correlation of Returns

Building up on Sentana and Wadhwani's feedback trading model, we utilise the models developed by Chau et al. (2011) to further test the existence and the link of feedback trading with different sentiment states. Yu and Yuan's (2011) and Kurov's (2008) findings suggest that the correlation between market returns and conditional volatility is positive when sentiment in the market is low, and almost flat for high sentiment levels. With respect to classic economic theory, this makes sense as higher degrees of risk (measured by conditional volatility) lead to a higher risk premium and, therefore, to a higher expected return. Flat correlation between conditional volatility and returns implies that the level of market rationality decreases when investors feel optimistic as more positive feedback traders enter the market.

Considering previous research, we would expect to obtain a stronger presence of positive feedback trading for high levels of sentiment (i.e. larger negative ϕ_1, or negative or smaller ϕ_0); however, we draw ambiguous conclusions from the results found analysing both, SENTIMENT and SENTIMENT^. It is important that we take into consideration the nature of the construction of the index before analysing the results as this impacts our interpretations. In this regard, both sentiment indices are constructed based on U.S. stock markets data representing the sentiment of U.S. investors and not a direct image of the sentiment in Bitcoin markets. Apart from the consideration of how close our sentiment indices represent the real level of sentiment, we discuss the implications and interpretations of the results next. We elaborate on the limitations of this approach in Section 10.4.

The unique nature of Bitcoin raises the question whether investor sentiment towards U.S. markets has an impact on Bitcoin markets and, if that is the case, what implications this relationship yields. In this regard, our results suggest a strong presence of positive feedback trading when the sentiment state is low advocating for a less rational market (as ϕ_{L1} is more negative than ϕ_{H1}). This evidence is found under both sentiment indices and all models, except for Model 3 under the orthogonalized index. The fact that the market exhibits a higher degree of irrationality when sentiment is low is not consistent with literature, but that does not necessarily imply that Bitcoin markets are not consistent with previous research. Instead, we find that when investors' expectations about the prospects of U.S. markets are negative, more feedback traders influence Bitcoin prices, which insinuates the possibility of unhappy U.S. investors shifting to Bitcoin markets and moving in opposite streams to well-established financial markets. This goes along the lines of Section 7.4 where Bitcoin is considered one of the ways to rebel against financial institutions. However, these results are constrained by the chosen time period as the evolution of the conceptualisation of Bitcoin throughout time is not taken into consideration. Furthermore, this result is contrary to recent findings that suggest that Bitcoin is negatively correlated to the CBOE volatility index (VIX), another indicator for investor sentiment, indicating that investors avoid Bitcoin markets in unsecure times (Jones, 2018). This result might be affected by the choice of time period as the fitted parameters may differ for different time periods.

In contrast, Model 3 under SENTIMENT^ shows a different conclusion than the other approaches (ϕ_{H1} is more negative than ϕ_{L1}). For this model, we find a closer alignment between theory and results as the level of positive feedback trading is higher for those periods of high sentiment advocating for less rationality when investors feel optimistic. Interestingly, Chau et al. (2011) state that Model 3 appears to be the preferred model to capture the variability of feedback trading over different sentiment states. As the parameter estimation for Model 3 complies most with the values that we would have expected, we confirm the results obtained by Chau et al. (2011).

This ambiguity in the results attained from the relationship between feedback trading and sentiment in the U.S. markets implies that there are multiple and numerous ways to study this relationship that advance the understanding of Bitcoin and add value for investors and economists. We confirm the inverse relationship between serial correlation and volatility uncovered by Sentana and Wadhwani (1992). Furthermore, we prove that this relationship varies over different sentiment states and its deeper study may unveil new discoveries to this unexplored market. To our knowledge, no previous research has transferred the theories discussed to a cryptocurrency context.

10.3. Contributions to Literature

Our thesis offers several interesting insights on the existing theories and models in behavioural finance literature by covering a scarcely investigated market. By applying Sentana and Wadhwani 's (1992) model (Model 1), we have been able to study the presence of serial correlation of returns and its relationship with volatility. The results yield conclusive answers to Research Questions 1 and 2 (See below).

RQ1*: Which type of feedback trading dominates Bitcoin markets?*

RQ2: *What is the relationship between feedback trading and volatility?*

With respect to *RQ1*, we find a predominance of positive serial correlation in Bitcoin returns indicating a larger presence of negative feedback trading for most of Bitcoin's existence up to today. This is, nevertheless, subject to certain conditions as discussed in Section 10.1. Furthermore, answering *RQ2*, we find an inverse relation between the autocorrelation of returns and volatility. This relationship is characterized by negative autocorrelation for high levels of volatility and vice versa.

The answers provided above shed light on the ongoing debate about the classification of Bitcoin as asset or currency. Bitcoin shares characteristics of assets, implying that market participants might use it as an asset. That investors use it as an asset, however, does not imply that it is an asset from a theoretical perspective.

The attempt to investigate the influence of sentiment on feedback trading yields, unfortunately, inconclusive results. We are, therefore, unable to provide a definite answer to RQ3 (see below).

***RQ3**: Does investor sentiment have an impact on feedback trading?*

The ambiguity in our interpretations of the results of Models 2, 3 and 4 additionally highlights this inconclusiveness. For instance, we find that an investors' optimistic state can either positively or negatively affect the presence of feedback trading across models. The same scenario is portrayed in the case of a pessimistic state. This ambiguity of responses allows for numerous interpretations and implications that open an opportunity to further explore the concept of sentiment in Bitcoin markets. Consequently, suggestions for future research are presented in Section 10.5.

10.4. Limitations

In this section we reflect upon the limitations we encountered and deem relevant for the interpretation of the results and for future research. Even though we base our research on well-established literature and investigation techniques, we identified several issues when applying these to Bitcoin markets. In the following, we identify first the main limitations linked to the sentiment indices and then the limitations related to the feedback trading models.

10.4.1. Limitations Related to the Sentiment Indices

The investor sentiment index developed by Baker and Wurgler (2006) is probably the most established sentiment index in the behavioural finance literature, with more than 6,500 overall citations. They further provide the sentiment index for the U.S. market on Wurgler's web page which facilitates its application but also provides little incentive for replicating the index.

When writing the thesis, the original index provided by Baker and Wurgler was only available up to 2014, we therefore constructed the index for our period of interest. It is, however, important to note that gathering the necessary data is cumbersome, with numerous different data sources involved, often with manually copying and pasting data. Determining the 'true' value for respective sentiment proxies is therefore a painstaking, if not impossible, endeavour. Considering the variability of data across different sources of data and the involvement of a great extent of manually gathering data for the six proxies, the resulting index must be taken with a grain of salt. This argument is further supported by the notion that it is highly improbable to remove all business cycle effects when regressing the proxies on macroeconomic variables. One must therefore be cautious when applying and interpreting the index.

Recently, Baker and Wurgler uploaded a new index up to 2018, consisting of only five variables (*pdnd, ripo, nipo, cefd, s*) instead of the originally proposed six variables (*pdnd, ripo, nipo, cefd, s, and turn*). This reduction of proxies is consistent with Baker and Wurgler's (2007) discussion on the data availability of the proxies, concluding that the index could possibly be constructed with fewer proxies. Comparing our raw proxies to the ones Baker and Wurgler obtained further strengthens our reasoning on the data availability in the previous paragraph: While the proxies that were readily available from a single data source match (e.g. *ripo* and *nipo*), the ones manually obtained or available at multiple data sources do not. The resulting indices therefore do not match as well, underlining the need for an index that facilitates consistency.

This ambiguity in results further highlights the importance of replicating work such as reproducing Baker and Wurgler's sentiment index. Baur et al. (2018), for example, encountered similar difficulties when attempting to replicate Dyhrberg's GARCH volatility analysis of Bitcoin (Dyhrberg, 2016). In this light, Baur et al. (2018) note that such replicative studies are conducted far too seldomly as these attempts encourage academic discourse and improve accuracy of research. We can only agree with this concern and call therefore for further replication studies of the Baker and Wurgler sentiment index. As Wurgler, conveniently, provides the sentiment index on a (more or less) regular basis, incentives to manually collect the data and construct the index are low. Given the cumbersome nature of replicating the index, it is comprehensible to simply download the readily available index when in doubt. Nonetheless, one must not underestimate the advantages of replication as elaborated on above.

Baker and Wurgler also did not clearly state every step of the methodology to construct the index, increasing the difficulty of replicating their work even more. For example, it does not become clear when reading the 2006 and 2007 papers, at which point one should standardise the proxies. That is, it is not explicitly stated whether Baker and Wurgler standardise the raw proxies before determining the first principal component or after. While our results are closer to the original index when standardising the raw proxies before conducting the PCA, our explained variance ratio seems too low compared to the one Baker and Wurgler obtain (c.f. Section 8.2.2.). The explained variance ratio of the unstandardized proxies, however, is closer to the numbers stated in the 2006 and 2007 papers. It would facilitate replicating the sentiment index, if Baker and Wurgler would explicitly state such methodological details in future research.

It is also imperative to bear in mind that we, analogous to Baker and Wurgler (2006), applied the sentiment index methodology to proxies capturing investor sentiment in the United States. We did so, as equivalent data for cryptocurrency markets was not yet readily available or did not exist. While it is already difficult to define ‘the’ cryptocurrency market, it is even more cumbersome to determine proxies substituting the ones that only make sense in established financial markets. For once, traditional financial markets tend to be bound to countries or continents. For cryptocurrencies, however, determining the true regional affiliation of markets remains challenging. Furthermore, defining a proxy equivalent to, for example, the NYSE turnover (*turn*) is not feasible as multiple digital exchange markets are competing for the position as dominant exchange which is changing at a rapid pace. To this end, capturing investor sentiment tailored to cryptocurrency markets did not make sense yet. Once cryptocurrency markets stabilise and mature, future research should attempt to establish suitable proxies adapted to the unique characteristics of cryptocurrency markets.

10.4.2. Limitations Related to the Feedback Trading Models

The original feedback trading model was amongst the firsts to quantify the existence of feedback trading in financial markets. The extension proposed by Chau et al. allowed investor sentiment to influence the demand of feedback traders and allowed for parameters varying with high and low levels of such sentiment. When applying the original and extended model to Bitcoin, we encountered several difficulties. For example, Chau et al. (2011) incorporated the sentiment index provided by Baker and Wurgler (2006), which is constructed on a monthly basis, into the feedback trading model with daily returns. It is thence necessary to convert the monthly index to daily. Chau et al. (2011) did not specify which approach was chosen for this conversion. As the results of the feedback trading models might vary substantially with the choice of approach to index conversion (see Section 8.3.3. for different valid approaches to the conversion from monthly to daily), future research utilising the Baker and Wurgler sentiment index for a scenario with daily data should make the approach chosen explicit.

The foundations of Baseline Model 1 provide, in addition, a framework that might be challenged by Bitcoin markets. The model's inherent assumption that rational investors trade on fundamentals might not hold in these markets as the discussion on fundamentals of cryptocurrencies is not settled yet. The acknowledgement of rational traders in an environment in which the value of the object under investigation is likely to be zero, would imply that no rational trader would enter this market voluntarily. This may invalidate our representation of rational traders as the ones trading on fundamentals. A more suitable definition of rational trading in this scenario could correspond to traders with the correct beliefs about the direction of prices, which does not necessarily involve fundamentals. The difference between trading on correct beliefs and rational speculation may lie on a very thin line. In this regard, the conceptualisation of rational trading on Bitcoin markets may not apply. A deductive approach, instead, could have had the potential to unveil additional characteristics about the price formation of Bitcoin that yield more conclusive and unbiased results.

10.5. Future Research

Existing literature has paid considerable attention to behavioural factors affecting the market. We find that the link between investor sentiment and returns is worth investigating. Bitcoin markets, however, are yet to be examined. Future research should explicitly focus on the relation between sentiment and feedback trading in cryptocurrency markets in general. In the previous sections we briefly mentioned limitations of current research. In this section, we call for research closing the gaps we identified.

As elaborated on in Section 9.2., the implied conditional autocorrelation indicates that negative feedback trading prevailed in the market while intuition would have suggested dominant positive feedback in recent years. We attribute this surprising result to the large time span of our data as the high price level of Bitcoin lets recent returns seem *relatively* small when compared to early returns. Future research should therefore investigate the relation between sentiment and feedback trading in Bitcoin markets over time, with particular attention to structural changes in the time series. Also, future research should differentiate between bear and bull markets as the market dynamics related to sentiment might change considerably. While this thesis investigated sentiment and feedback trading in Bitcoin markets, the potential structural changes of the market over time call for further research to investigate this relation over time.

Furthermore, we assume that price dynamics across Bitcoin market exchanges feature approximately the same trading characteristics. We, therefore, chose to analyse Bitcoin as an aggregate market as compiled by Yahoo Finance. To investigate sentiment and feedback trading in Bitcoin markets, one would need to repeat the analysis undertaken in this thesis for a representative number of Bitcoin market places. Bitcoin markets might exhibit different dynamics not only across countries and currencies, but also across trading platforms as different regulations and fee schemes might apply. This approach would also allow to study the influence of regulatory measures on trading. In addition, it would be particularly interesting to compare sentiment and feedback trading across various cryptocurrencies. Bitcoin as the most popular cryptocurrency by market capitalisation (c.f. Section 3) was the apparent choice. As other markets potentially exhibit very different dynamics, future research should analyse these with respect to sentiment and feedback trading.

In Section 10.4., we referred to the scarcity of replicative studies in economics. Considering the ambiguity in replicating the sentiment index, we endorse the point Baur et al. (2018) make. Future research should make the effort and attempt to replicate Baker and Wurgler's sentiment index to encourage academic discourse and improve its replicability. Furthermore, once cryptocurrency markets stabilise and mature, research should address adequate sentiment proxies adapted to the unique characteristics of cryptocurrency markets. As discussed in Section 8.2., we decided to directly replicate the sentiment index reflecting U.S. market sentiment as determining appropriate sentiment proxies for cryptocurrencies is not yet feasible.

Similarly, we could have chosen different indicators of investor sentiment than the Baker and Wurgler sentiment index. The consideration of, for example the VIX, Google searches or the CCSIX might yield interesting results worth to investigate. It would thence be compelling to compare sentiment and feedback trading across different indices and proxies to investor sentiment. To this end, the reliability of these indices with respect to predictive power and compliance with each other should be assessed first.

11. Conclusion

When feedback trading and sentiment coexist in financial markets, speculation can reach unlimited levels. Bitcoin markets are no exception and research to this date is limited. In this thesis we aimed to identify the presence of feedback trading in Bitcoin markets by studying the serial correlation of returns and examine how it relates to price volatility. In addition, we attempted to measure the level of investor sentiment in U.S. markets and investigate its effect on feedback trading.

Based on a quantitative analysis, we conclude that returns tend to exhibit positive serial correlation for low levels of volatility. When volatility levels rise, however, the presence of positive feedback trading becomes more dominant displaying negative return autocorrelation. This thesis unveiled Bitcoin market dynamics that are characteristic of many other financial markets, with an inverse relationship between serial correlation of returns and volatility. We confirm Sentana and Wadhwani's (1992) findings when applying their model to a new market. Our results indicate that feedback trading persists in Bitcoin markets with a dominating positive serial correlation of returns. We believe, however, that further research should be conducted across various periods of time as feedback and speculation dynamics are likely to change over time.

When investigating the effects of investor sentiment on feedback trading following Chau et al. (2011), we find inconclusive results that are mainly driven by the intrinsic difficulty of measuring sentiment. The effects sentiment exerts on Bitcoin prices, although sometimes apparent, remain an empirical incognita for numerous reasons. The most important one may still well be the difficulty in approaching and obtaining sentiment measures, especially in a market that is still evolving. For this reason, we call for future research of both the measurement of investor sentiment proxies and its effect in Bitcoin markets.

Based on our conclusions, investors should bear in mind that positive feedback trading strategies are likely to bring instability to Bitcoin markets. When markets are agitated, and price fluctuations are rough and persistent, the most intelligent investment decision might be to not participate in the market. If feedback trading strategies are also enhanced by erroneous beliefs, Bitcoin markets are likely to exhibit bubble dynamics. Investors participating in these markets should therefore do so with caution.

Appendix

A.1: Eigenvalues and Eigenvector

Eigenvectors - SENTIMENT					
ripo	*nipo*	*s*	*cefd*	*turn*	*pdnd*
0.38605564	0.30291299	-0.4444716	-0.7417872	0.10374416	-0.0252726
0.31406601	-0.203268	-0.6011983	0.51080104	0.46865911	-0.134336
-0.4820872	0.59308942	-0.2345838	0.15102525	0.26333961	0.51831548
0.52915217	0.67012239	0.33042983	0.34730704	-0.0728659	-0.1892577
0.33271206	-0.2169704	0.47102537	-0.1339924	0.58078901	0.51487068
-0.3594665	0.13795146	0.23436564	-0.1656784	0.59801565	-0.6416806
Eigenvalues - SENTIMENT					
1.89924727	0.47856527	1.14016235	0.81481895	0.72489981	0.9963604

Eigenvectors - SENTIMENT^					
ripo	*nipo*	*s*	*cefd*	*turn*	*pdnd*
0.19636054	0.22704176	0.11006657	0.59935615	-0.7338566	0.00256899
0.51050428	-0.7140801	-0.010407	0.0108592	-0.0753626	0.47283104
0.57342335	0.58125133	-0.432625	-0.0255248	0.248541	0.2893856
0.53973737	0.10690031	0.71284155	-0.1404447	0.16838824	-0.3755443
0.17955864	-0.2847382	-0.3791114	0.53073042	0.33448124	-0.5911048
-0.2201269	0.09047081	0.38567359	0.58189627	0.50375591	0.44971299
Eigenvalues - SENTIMENT^					
1.49098105	0.64327267	0.66583466	0.85570527	1.11948428	1.27877612

A.2: GARCH Model Selection

GARCH

MLE	p(0)	p(1)	p(2)	p(3)	p(4)
q(0)	0	0	0	0	0
q(1)	-3683	-3036	-3027	-3017	-3014
q(2)	-3271	-3036	-3027	-3017	-3013
q(3)	-3205	-3036	-3027	-3017	-3013
q(4)	-3159	-3036	-3027	-3017	-3013

aic	p(0)	p(1)	p(2)	p(3)	p(4)
q(0)	0	0	0	0	0
q(1)	7372	6081	6065	6046	6042
q(2)	6549	6083	6067	6048	6042
q(3)	6420	6085	6069	6050	6044
q(4)	6329	6087	6071	6052	6046

bic	p(0)	p(1)	p(2)	p(3)	p(4)
q(0)	0	0	0	0	0
q(1)	7390	6105	6095	6082	6084
q(2)	6574	6113	6103	6090	6091
q(3)	6450	6121	6111	6098	6099
q(4)	6366	6129	6119	6106	6107

TGARCH

MLE	p(0)	p(1)	p(2)	p(3)	p(4)
q(0)	-3980	-3592	-3591	-3586	-3583
q(1)	-3701	-3043	-3042	-3037	-3037
q(2)	-3249	-3043	-3042	-3031	-3031
q(3)	-3177	-3043	-3042	-3031	-3031
q(4)	-3137	-3043	-3042	-3031	-3031

aic	p(0)	p(1)	p(2)	p(3)	p(4)
q(0)	7967	7191	7192	7183	7180
q(1)	7410	6097	6097	6088	6089
q(2)	6508	6099	6099	6079	6079
q(3)	6365	6101	6101	6081	6081
q(4)	6288	6103	6103	6083	6083

bic	p(0)	p(1)	p(2)	p(3)	p(4)
q(0)	7985	7215	7222	7220	7223
q(1)	7434	6127	6133	6131	6137
q(2)	6538	6135	6141	6127	6133
q(3)	6401	6143	6149	6135	6141
q(4)	6330	6151	6157	6143	6149

GJR-GARCH

MLE	p(0)	p(1)	p(2)	p(3)	p(4)
q(0)	-3925	-3526	-3525	-3521	-3518
q(1)	-3676	-3036	-3027	-3017	-3014
q(2)	-3267	-3036	-3027	-3017	-3013
q(3)	-3203	-3036	-3030	-3017	-3013
q(4)	-3157	-3036	-3027	-3017	-3013

aic	p(0)	p(1)	p(2)	p(3)	p(4)
q(0)	7857	7061	7060	7053	7050
q(1)	7359	6082	6067	6048	6044
q(2)	6544	6084	6069	6050	6044
q(3)	6419	6086	6075	6052	6046
q(4)	6329	6088	6073	6054	6048

bic	p(0)	p(1)	p(2)	p(3)	p(4)
q(0)	7875	7085	7090	7090	7092
q(1)	7383	6113	6103	6090	6092
q(2)	6574	6121	6111	6098	6098
q(3)	6455	6129	6124	6106	6106
q(4)	6371	6137	6127	6114	6114

EGARCH

MLE	p(0)	p(1)	p(2)	p(3)	p(4)
q(0)	0	0	0	0	0
q(1)	-4160	-3009	-3006	-2996	-2994
q(2)	-3545	-3003	-3003	-2993	-2989
q(3)	-3464	-2990	-2990	-2990	-2989
q(4)	-3358	-2990	-2990	-2989	-2988

aic	p(0)	p(1)	p(2)	p(3)	p(4)
q(0)	0	0	0	0	0
q(1)	8329	6028	6024	6007	6005
q(2)	7100	6018	6020	6003	5997
q(3)	6940	5994	5996	5998	5999
q(4)	6730	5996	5998	5999	5997

bic	p(0)	p(1)	p(2)	p(3)	p(4)
q(0)	0	0	0	0	0
q(1)	8353	6058	6060	6049	6053
q(2)	7131	6054	6062	6051	6051
q(3)	6977	6036	6044	6052	6059
q(4)	6773	6044	6052	6059	6064

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