Behavioural Finance and Cryptocurrencies

Studies of Behavioural Finance in Cryptocurrency Markets

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Declaration

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Abstract

Interest in cryptocurrencies among researchers has been on the rise as this novel asset class continues to attract significant fund flows from retail and as well as institutional investors due to the promising returns it has offered historically. While the behavioural biases and performance of traders have been studied extensively in traditional financial markets, the literature on these topics within the crypto space remains lacking.

This thesis aims to provide insight into the behavioural characteristics of cryptocurrency traders by investigating two behavioural biases that have been widely explored in traditional financial markets, namely, the disposition effect and the gambler's fallacy. Moreover, I investigate the impact of market sentiment on trader performance and activity in the crypto space using an alternative on-chain measure of sentiment.

Regarding the study on the disposition effect, I apply the popular disposition spread metric of Odean (1998) on a unique data set of individual cryptocurrency traders from an anonymous exchange and find significant evidence of an anti-disposition effect. In analysing the disposition effect across market conditions, trader experience, and age groups in the cryptocurrency market, the study finds that neither market trends nor average trade size significantly alter traders' biases in realising gains or losses. Younger traders, especially those aged 18-30, exhibit a unique positive disposition effect, suggesting quicker gains realisation. Conversely, older traders display a reduced anti-disposition effect, indicating that the tendency to hold losing investments decreases with age. The study aligns with existing literature in suggesting that experience mitigates behavioural biases, evidenced by the consistent patterns observed in both the cryptocurrency and traditional financial markets.

In the second study, I investigate whether traders exhibit trend-chasing behaviour by examining the relation between traders' past performance and their future trade size. Specifically, those who exhibit the gambler's fallacy are likely to increase their trade size after experiencing poor past performance as they double down on future investments to make up for poor past performance. Alternatively, those who exhibit the hot-hand fallacy are likely to increase their trade after experiencing positive past performance as they believe that good performance will persist into the future. My results show that crypto traders exhibit the gambler's fallacy, such that they are likely to increase their position size after exhibiting poor past performance, suggesting that they expect a trend reversal.

In the final study, I investigate the impact of market sentiment on trader performance and activity. While the literature has mainly focused on text-based models to gauge market sentiment, I employ an alternative on-chain metric called the Net Unrealised Profit Loss (NUPL), which is a measure of accounting of the overall state of profitability of a blockchain network. A positive (negative) NUPL suggests that the blockchain network is in a state of profit (loss) and thus nearing a market top (bottom). Hence, this metric offers insight into the general degree of market sentiment based on fundamental on-chain data. My findings show that changes in sentiment positively impact the total return experienced by traders. Moreover, traders experience the highest levels of total returns when market sentiment is very high. Second, traders who react immediately to market sentiment, especially when sentiment is very high, are likely to realise higher positive returns. Third, higher levels of market sentiment lead to larger future trade sizes; hence, traders increase their exposure when market sentiment is high. Finally, I report weak evidence supporting the notion that higher levels of market sentiment result in traders modifying their trade size. This suggests that a change in trade size is agnostic to market sentiment. For robustness, I also adopt the VIX, a common equity market volatility index, to measure sentiment in the cryptocurrency market; however, the results showed no consistent impact, highlighting the need for developing a sentiment measure specifically designed for the unique characteristics of the cryptocurrency market.

The concluding chapter reviews the main findings of this thesis and discusses avenues for future research.

Chapter 1

Overview of Cryptocurrencies

Chapter 1

Overview of Cryptocurrencies

In 2008, the blockchain was presented and subsequently implemented in 2009 (Zheng et al. 2018, Hashemi Joo et al. 2020) by the entity known as Satoshi Nakamoto in the so-called Bitcoin cryptocurrency. The blockchain is a distributed ledger that records peer-to-peer transactions as blocks on the chain with an immutable timestamp. This relies on a consensus algorithm that is built up on asymmetric cryptography and distributed among various nodes, as well as unique hashes, which allows for a decentralised environment free of third party validators. As a result, blockchain technology lowers transaction costs in a secure way.

An example of how blockchain technology works, is demonstrated below through Bob's purchase of a laptop from Alice.

- Bob places an order to purchase a laptop from Alice, creating a transaction from Bob to Alice. This transaction will most likely occur along many other transactions on the blockchain. Bob's transaction is distinguished by a timestamp and stored in a block with the hash of previous transactions, and transaction data.

- A network of computers verify Bob's transaction by going through a mathematical process to verify the entire block. A unique hash is then given to the block, along with the hash of the previous block, and is subsequently added to the blockchain.

According to Zheng et al. (2018), Hashemi Joo et al. (2020), four key characteristics define blockchain technology

- **Decentralisation** This is the process of transacting in the absence of centralised authority.
- **Immutability** This refers to the certitude that altering already verified transactions is very complex and/or impossible.
- **Auditability** This is the ability of tracing verified transactions using the block data.
- **Anonymity** This is the possibility of being anonymous to a certain extent. Privacy is not always guaranteed as per intrinsic constraints of blockchain technology.

1.1 Cryptocurrency

A cryptocurrency is used to transact on a peer-to-peer basis through exchange networks (DeVries 2016). The difference between a cryptocurrency, such as Bitcoin, and electronic money is that cryptocurrencies are produced via the internet, while electronic money is deposited into bank accounts through banks (Bondarenko et al. 2019). Changes in the global economic environment have driven an increase in the demand for Bitcoin, despite Bitcoin's structure remaining unchanged since its launch (DeVries 2016). One main driver in this demand for Bitcoin is its exponential increase in price since its widespread recognition in 2017 (Conti et al. 2018, Gencer et al. 2018). Decentralisation was another main driver of this increase in demand as many users liked the idea of being in control of their own assets rather than relying on a centralised authority (Conti et al. 2018, Gencer et al. 2018). The growth of digital technologies that make daily processes more efficient has been another driver of increased demand in the cryptocurrency space (Bondarenko et al. 2019). A plethora of cryptocurrency related services and platforms have sprung into existence in recent years, such as Coinmarketcap (CMC). CMC displays information on cryptocurrencies, as well as the broader market. For example, as of November 22, 2022, Bitcoin has a market capitalisation of just over $300 Billion USD and a 38.6% market dominance. Whereas the market capitalisation for the broader cryptocurrency industry is just over $800 Billion USD for a total of about 21,832 cryptocurrencies. Going through the historical snapshot on the CMC website, one can see that on May 05, 2013, only 10 cryptocurrencies were being tracked on CMC.

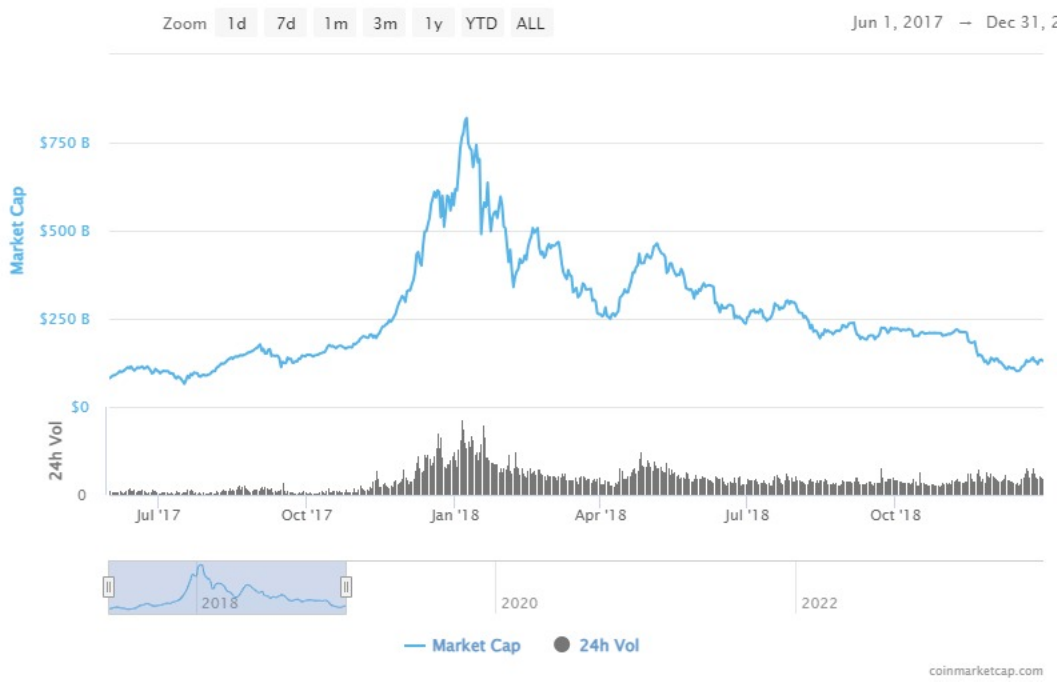


Figure 1.1: Total Market Capitalisation and Volume Traded of Cryptocurrencies, According to Coinmarketcap

Figures 1.1 and 1.2 clearly show how the market capitalisation of cryptocurrencies peaked in between the end of 2017 and early 2018 in the so-called *2018 cryptocurrency crash* at just over $800 Billion USD and the subsequent crash in value. This is dwarfed by the close to $3 Trillion USD market capitalisation reached in November 2021.

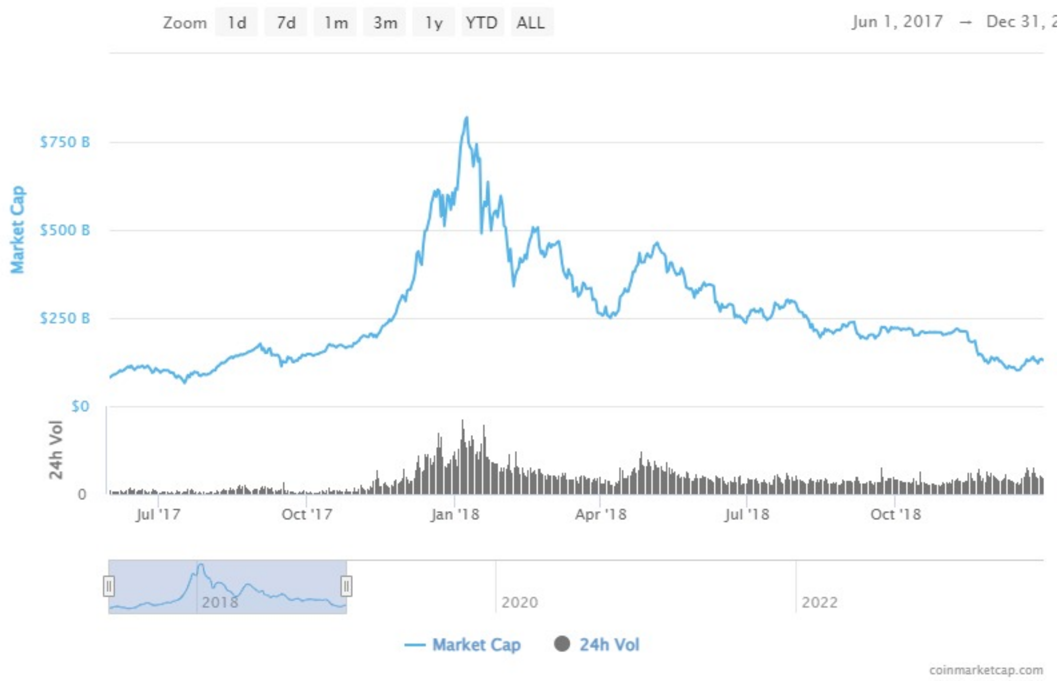


Figure 1.2: Total Market Capitalisation and Volume Traded of Cryptocurrencies, Which Covers the Sample Period Only, According to Coinmarketcap

1.2 Applications of Cryptocurrencies

Applications of cryptocurrencies continue to develop as awareness grows and as many daily activities now rely on cryptocurrencies due to their efficiency compared to commodity services, with the most popular use cases being finance and payment services related (Nagpal 2017, Berentsen & Schär 2018). These services include trading cryptocurrencies on exchanges, purchasing goods from vendors that accept such payments, and sending or receiving money (Nagpal 2017).

Cryptocurrencies are accessible anywhere around the world which makes it easy for investors to invest in digital assets and try to make profits (Chuen et al. 2017). Market conditions such as supply and demand, determine what each cryptocurrency is worth, analogous to traditional markets (Nagpal 2017). Mikhaylov (2020) states that investor sentiment causes volatility in the cryptocurrency market, as increasing cryptocurrency prices ensues positive investor sentiment which leads to an increase in demand. This volatility can make cryptocurrencies seem more lucrative than other investment opportunities such as stocks and foreign exchange, which have lower volatility (Chuen et al. 2017). Bitcoin derives its intrinsic value from its limited supply, capped at 21 million Bitcoins, which makes it scarce, and therefore an important factor in affecting its price (Brekke & Fischer 2021). According to Baur et al. (2018), the main reason individuals purchased Bitcoin was speculative investing. Multiple platforms exist for users to purchase cryptocurrencies, such as cryptocurrency exchanges, banks that offer their clients opportunities to buy cryptocurrencies, and vending machines (Brekke & Fischer 2021). Anyone equipped with internet access is qualified to invest in cryptocurrencies, which makes them even more attractive to users (Brekke & Fischer 2021). Therefore, ease of investment was part of the reason why the market capitalisation of cryptocurrencies rose, which was due to many individuals and institutions quickly adopting digital assets.

Investors can trade their purchased cryptocurrencies on various exchanges to make profits using different trading strategies (Muftic 2016). According to Fang et al. (2022), there are three types of trading strategies

- **Technical trading** used to determine current or future market conditions by analysing historical transactions.
- **Fundamental trading** used to determine when to enter and exit positions, by analysing events that affect markets.
- **Quantitative trading** used in a similar manner to a technical strategy, but employs software to perform trades.

Traders can also convert their current cryptocurrency pair positions to different cryptocurrency pairs directly, without having to convert to fiat currencies and then back again to cryptocurrencies. For example, one can exchange BTC/SOL to ETH/USDT, directly. Advantages of trading cryptocurrencies include markets that operate 24 hours a day all year round, pseudonymous trading, and the lack of centralised institutional intermediaries to process transactions for a fee (Fang et al. 2022).

Many businesses, most notably GameStop and Baskin Robins, are accepting cryptocurrency payments for their goods and services, regardless of whether these purchases are done through online shopping, or in person at shop locations (Sukarno et al. 2020). Cryptocurrencies are border-less, which means anyone around the world can send and receive them through their cryptocurrency wallet. All this is done in the absence of trust between any two users due to the nature of blockchain technology (Muftic 2016). Sending money across the world on networks such as the Tron blockchain, would entail lower transaction fees than other methods, such as through Western Union. In addition to that, sending cryptocurrencies from one wallet to another is fast and normally requires between 1-60 minutes to be transferred (Titov et al. 2021).

1.3 Mining

Cryptocurrency mining is one way in which cryptocurrencies like Bitcoin can be released into market circulation (Aljabr et al. 2019, Mukhopadhyay et al. 2016). A block is validated when miners solve a complex mathematical puzzle which contains the hash of the previous block, the hash of transactions in the current block, as well as a Bitcoin address to which rewards are then paid out (Eyal & Sirer 2018). A node, usually a powerful computer, is then used to create a new block with a unique hash (Eyal & Sirer 2018). Bitcoin miners have to compete amongst each other to be the first at solving the complex mathematical puzzle for each block in a process known as Proof-of-Work, in order to be rewarded a fixed amount of Bitcoins (Eyal & Sirer 2018). This process occurs approximately every 10 minutes, and that's how new Bitcoins are released into the market (Eyal & Sirer 2018). Another mechanism to create cryptocurrencies is known as Proof-of-Stake, which is faster and uses less energy, which makes it a more efficient substitute to Proof-of-Work (Popov 2016).

1.4 Characteristics of Cryptocurrencies

1.4.1 Decentralisation

Decentralisation refers to the users being in control of their assets, rather than an institution (Fang et al. 2022). Most users turn to cryptocurrencies due to their decentralised characteristics (Radivojac & Grujić 2019). Users also enjoy the control over their assets in a decentralised system, where they might not have to worry about getting the full amount of their money in case of an institution going bankrupt, as opposed to a centralised system (Radivojac & Grujić 2019). This also means that users can purchase goods freely without their governments knowing about it, which in turn, has raised speculation by institutions, such as the FBI, that illegal activities are carried through cryptocurrencies (Radivojac & Grujić 2019). The use of cryptocurrencies solely cannot happen, since countries would not be able to track their citizens' incomes, which makes tax evasion a possibility (Frebowitz 2018). This can change if governments start to recognise and support the use of cryptocurrencies, and find ways to track the money inflows and outflows of their citizens (Frebowitz 2018).

1.4.2 Security of Cryptocurrencies

Bitcoin's security is composed of the blockchain, mining, key management, and consensus (Conti et al. 2018, Ghosh et al. 2020, Bucko et al. 2015, Quamara & Singh 2022). The network transaction history is shown through the public ledger which is part of the blockchain (Conti et al. 2018, Ghosh et al. 2020). Hence, it is close to impossible to tamper with information on the blockchain, which ensures the security of the network (Conti et al. 2018, Bucko et al. 2015). Bitcoin miners are essential in the security of the network as they are the ones that validate each transaction through the Proof-of-Work (PoW) decentralised consensus algorithm (Conti et al. 2018). It is expensive and time consuming to start mining Bitcoin, which gives miners the incentive to be fair and avoid foul play, since an infraction could lead the miner being banned from the Bitcoin network (Conti et al. 2018). PoW also eliminates the possibility of a Bitcoin user with large Bitcoin holdings to have full control of the blockchain (Conti et al. 2018). Key management is when a user takes responsibility for storing their public and private keys, securely. The private key, normally stored offline, could enhance security as a hacker would would need that information to digitally sign off transactions (Conti et al. 2018). The use of a public key does not risk security, as that is used for sending and receiving assets (Conti et al. 2018). Despite PoW being highly scalable and decentralised, it still faces potential attacks discussed by Conti et al. (2018), which include

- **Double spending** the act of spending the same Bitcoin twice.
- **Greater than 50% hashpower** the act of taking control of over 50% of the hashrate.
- **Finney attack** a dishonest miner presents a pre-mined block in order to double spend.
- **One confirmation attack** a combination of the Finney attack and double spending.

- **Selfish mining** the act of taking advantage of Bitcoin forking in order to get unfair rewards.

- **Block withholding** a miner presents one particular PoW rather than the full PoW.

- **Brute force attack** the act of private mining on blockchain fork to eventually double spend.

1.4.3 Trust Factors of Cryptocurrencies

Trust is the act of being vulnerable to the actions of another party, with the hope that the other party will meet the expectation of the trustor without being monitored (Marella et al. 2020, Bucko et al. 2015). The trust of cryptocurrency users is determined by their trust in the underlying technology such as the blockchain, which differs from their trust of traditional financial institutions, which entails trusting legislation and central authorities (Marella et al. 2020). Some factors that contribute to the trust of cryptocurrencies are that the blockchain does not allow for previous information to be falsified, cryptocurrency wallets can be stored on external software, and cryptocurrency exchanges require verification before funds are transferred to other wallets (Marella et al. 2020, ur Rehman et al. 2019). Other attributes that can contribute to users' trust in cryptocurrencies, such as Bitcoin, as stated by Marella et al. (2020) are

- **Speed** users reported that Bitcoin transfers are faster than fiat currency transfers.

- **Immutability** information on the blockchain is impossible to tamper with.
- **Openness** transaction information is public.

Some other factors that Marella et al. (2020) states could make Bitcoin more trustworthy are

- **Stability** having a more stable Bitcoin price.
- **Regulation** Bitcoin should be regulated.
- **Security** improve the security of exchanges and wallets.
- **Knowledge** knowledge of Bitcoin and the underlying technology.

1.4.4 Privacy in Cryptocurrencies

One reason cryptocurrencies are successful is due to the privacy involved. An advantage of using Bitcoin is that each Bitcoin user has a pseudonymous identity which makes it hard to identify Bitcoin holders, unless a Bitcoin's public keys or hashes are exposed (Conti et al. 2018). Other cryptocurrencies, such as ZeroCash, meet higher privacy levels by using a method known as Zero-Knowledge-Succinct Non-Interactive Argument of Knowledge, and withhold important transaction information, such as the amount sent and the recipient address (Conti et al. 2018, Alsalami & Zhang 2019, Ghosh et al. 2020). Another cryptocurrency with high privacy levels is Monero which uses stealth addresses and ring signatures that hide identities of senders and receivers (Alsalami & Zhang 2019). Ring signatures are digital signatures in the absence of trusted managers, whereby any individual in a group can sign on behalf of the group (Alsalami & Zhang 2019). Monero has gone even further to create Ring Confidential Transaction, which reduces transaction fees as well as hides transaction amounts (Alsalami & Zhang 2019).

Bitcoin's pseudonymous address can be compromised through various methods, such as monitoring IP addresses, which can expose the user's identity (Conti et al. 2018). One way to improve privacy issues is though peer-to-peer mixing protocols (Conti et al. 2018). This is the process of breaking down users' funds into small amounts and randomly group them with funds from different users, in such a way that every user appears to have completely different funds than what they truly own (Conti et al. 2018). MixCoin employs the mixing protocol by allowing users to send certain amounts of cryptocurrencies and receiving an equivalent amount back from a different user, which ensures anonymity (Conti et al. 2018).

1.4.5 Electricity Consumption

Carbon and other natural gas emissions from cryptocurrency related activities, like mining, have raised concerns over their environmental impacts (Badea & Mungiu-Pupzan 2021, Li et al. 2019, Stoll et al. 2019, Gallersdörfer et al. 2020). Between 2018-2019, the Bitcoin network is estimated to have consumed 87.1 terawatt-hours of electricity, approximately equivalent to the electricity consumption of Belgium according to the Cambridge Bitcoin Electricity Consumption Index (CBECI) and Bitcoin Energy Consumption Index (BECI) methodologies (Badea & Mungiu-Pupzan 2021). Some estimated suggest that \$1 worth of Bitcoin mining, resulted in \$0.49 worth of climate damages in the United States of America in 2018 (Badea & Mungiu-Pupzan 2021). As the price of Bitcoin increases, Bitcoin miners do not seem eager to stop their activities, hence, consuming more energy (Badea & Mungiu-Pupzan 2021). Countries such a China are desirable destinations for Bitcoin miners since electricity is cheaper since it is mainly obtained through burning coal, which emits more carbon emissions than alternative sources (Badea & Mungiu-Pupzan 2021). Similarly, other cryptocurrencies that rely on PoW, such as Monero, also consume high levels of electricity (Badea & Mungiu-Pupzan 2021).

Nevertheless, Bitcoin appears to be more environmentally and economically friendly than paper money, banking systems, and gold mining (McCook 2014). Total carbon emissions by the banking system hover around 387 million tons while Bitcoin emits around 0.75 million tons, according to research by the CoolClimate Network at the University of California, Berkeley (McCook 2014).

1.4.6 Perceived Risk of Cryptocurrencies

Risk perception is the possibility of negative consequences of using a product or service, as defined in the Information Systems (IS) industry (Chen & Farkas 2019). Adoption of modern modern technologies have been impacted by risk perceptions of technology as shown by past studies (Abramova & Böhme 2016). Six risks were analysed by Abramova & Böhme (2016), which include market risk, counterparty risk, transaction risk, operational risk, privacy risk, and legal and regulatory risk, and have shown limitations to Bitcoin adoption due to risk of loss of funds and lack of consumer protection. To limit these risks, exchanges like Coinbase have started to insure some security threats by working with insurance companies (Abramova & Böhme 2016). Abramova & Böhme (2016) further state that users want decentralised cryptocurrencies to be regulated, in order for users to be legally protected. In addition to that, they also show that users who consider adopting Bitcoin, have a perceived risk due to Bitcoin's complicated system (Abramova & Böhme 2016). Furthermore, they show that decentralisation has added to the perceived risk of users due to the lack of a central authority or the legal protection of users (Abramova & Böhme 2016).

1.5 Cryptocurrency Trader Bias and Market Sentiment

The crypto space has undoubtedly attracted many retail traders due to the significant returns that dwarf those of other asset classes. The literature on retail traders in general has highlighted the prominence of behavioural biases in, and the impact of market sentiment on trader decision making. These, while not specific to the crypto asset class, may be considered as risks or explanatory factors of trader decisions and their overall performance. Hence, by shedding light on the behavioural biases among cryptocurrency traders and how their decision making process may be impacted by external factors, such as sentiment, one can better understand and manage risk and make better informed trading decisions.

As such, this thesis aims to offer insight into the behavioural characteristics of cryptocurrency traders by investigating two behavioural biases that have been widely explored in financial literature: the disposition effect and the gambler's fallacy. Moreover, this thesis also studies the impact of market sentiment on trader performance and activity in the crypto space.

1.5.1 Disposition Effect in Cryptocurrency Markets

Research question 1: Do cryptocurrency traders exhibit the disposition effect?

In the first study, I investigate whether traders in the cryptocurrency space exhibit the disposition effect, which is defined as the tendency of an investor to realise gains while holding on to losses (Shefrin & Statman 1985). Many researchers have examined this bias and have found that it negatively impacts trader performance (Odean 1998, Grinblatt & Keloharju 2001). Nonetheless, our understanding of the disposition effect within the crypto space remains limited, especially given that this novel asset class is governed by anonymity, decentralisation, and relatively high volatility (Baur et al. 2018, Hu et al. 2019, Liu & Tsyvinski 2021). In other words, are crypto traders more likely to hold on to their investments as this industry continues to develop and innovate? Or are they likely to realise gains quickly given the heightened level of market volatility?

Using a unique data set of individual cryptocurrency traders from an anonymous exchange, I apply a popular methodology developed by Odean (1998), called the disposition spread that estimates the tendency of an individual to realise a gain relative to a loss. I find evidence of anti-disposition effect among cryptocurrency traders. Specifically, I find that this effect is pronounced when calculating the disposition spread on weekly, monthly and quarterly frequencies. Moreover, the anti-disposition effect is more evident for traders in age groups of up to 50 years old and decreases thereafter. This suggests that younger traders are more likely to hold on to their winning positions. There is also an element of learning and experience, as older traders tend to behave in a less biased fashion, consistent with much of the behavioural finance literature. In general, my results show that the behaviour of cryptocurrency traders differs than what has been reported in traditional financial markets with respect to the disposition effect.

1.5.2 Gambler's Fallacy and the Hot Hand Fallacy in the Cryptocurrency Market

Research question 2: Are cryptocurrency traders more prone to exhibit the gambler's fallacy or hot hand fallacy?

Individuals who exhibit the hot hand fallacy believe in positive autocorrelation of a non-autocorrelated sequence of events, where they expect a historical pattern to continue into the future. On the other hand, individuals who are prone to the gambler's fallacy believe in a negative autocorrelation or mean-reversion relationship to exist within a non-correlated random sequence. Several studies have shown that both of these biases can have negative effects on the performance of traders (Brown et al. 1996, Chevalier & Ellison 1997, Sirri & Tufano 1998, Goetzmann & Kumar 2008).

Traditional financial markets enjoy a higher level of transparency and abundance of fundamental information compared to cryptocurrency markets. This is because many cryptocurrencies are decentralised with no identifiable entity that publishes information periodically. As a consequence, such an environment may result in traders exhibiting trend-chasing behaviour in the form of their the hot hand fallacy or the gambler's fallacy.

Using a proprietary data set of transactions from an anonymous cryptocurrency exchange, I investigate whether traders exhibit trend-chasing behaviour by examining the relation between traders' past performance and their future trade size. Thus, those who exhibit the gambler's fallacy are likely to increase their trade size after experiencing poor past performance as they double down on future investments to make up for poor past decision. On the other hand, if the relation between past performance and future trade size is positive, then this suggests evidence of the hot hand fallacy, as traders believe that good performance will persist into the future.

My findings show that crypto traders exhibit the gambler's fallacy, such that they are likely to increase their position size after exhibiting poor past performance. Additionally, I find evidence of traders trading in the opposite direction of the market, which suggests that they expect a trend reversal. This further supports evidence of the gambler's fallacy.

1.5.3 The Impact of Sentiment on Trader Performance and Activity in the Cryptocurrency Market

Research question 3: Does market sentiment affect the performance and trading activity of cryptocurrency traders?

The literature has presented significant evidence highlighting the impact of news and sentiment on financial markets (Peterson 2016). Several studies have shown that cryptocurrency prices are driven by public excitement as manifested in opinions and blog posts published on social media platforms (Kristoufek 2013, Shen et al. 2019, Shiller 2020, Kraaijeveld & De Smedt 2020, Naeem, Mbarki, Suleman, Vo & Shahzad 2021, Naeem, Mbarki & Shahzad 2021). This has motivated researchers to focus on text-based sentiment metrics to measure the impact of market sentiment — as published via social media platforms, including *Reddit* (Nasekin & Chen 2020) and *Twitter* (Guégan & Renault 2020) — on price discovery in the crypto market. These studies have overwhelmingly shown that price movements and trends in the crypto market, while they cannot be explained by any identifiable fundamental factors, are driven by market sentiment.

Despite the evidence presented in these studies on the impact of sentiment on cryptocurrency prices, very little research has been conducted on the effects of sentiment on decision making at the trader level. Therefore, I take this opportunity to address this gap in the literature by investigating the degree to which market sentiment affects the performance, trade size, as well as the frequency of trading among crypto traders.

I adopt an alternative proxy to measure market sentiment called the Net Unrealised Profit/Loss (or NUPL), which captures the difference between the on-chain cost basis and market value of digital assets on a blockchain network. More specifically, the on-chain cost basis is an average price that captures the value of a cryptocurrency at the time it last moved on the blockchain. On the other hand, the market value takes the current price of the cryptocurrency multiplied by the number of coins in circulation. The difference between these two values may give an indication whether and what proportion of the coins on the network are in a current state of unrealised profit or loss. Hence, NUPL is a measure of accounting that compares the contemporary value of the blockchain relative to its on-chain cost basis. A positive NUPL suggests that the blockchain network is in a state of profit, and vice-versa. Moreover, the further the NUPL deviates from zero, the more likely the market is getting closer to a top or bottom. When a growing percentage of coins on a blockchain start carrying an unrealised profit, this implies a higher level of market sentiment and a greater likelihood that traders will start taking profits.

This study reports several findings that underscore the effect of market sentiment on crypto trader performance and trading activity, and contributes to the literature on how market sentiment affects decision-making in a market that is governed by an ambiguous regime. First, I find that changes in lagged market sentiment positively impact the total return experienced by traders. Moreover, traders experience the highest levels of total returns when market sentiment is very high. Second, traders who react immediately to market sentiment, specifically when the overall market sentiment is very high, are likely to realise higher positive returns. Third, I find that positive changes in market sentiment lead to larger future trade sizes; hence, traders increase their exposure when market sentiment is high. Nevertheless, I find no evidence that a change in sentiment leads to a *change* in trade size. This means that a change in trade size is agnostic to changes in market sentiment, and thus traders do not dynamically alter their exposure according to variations in market sentiment.

1.6 Contribution

This thesis contributes to the growing literature on cryptocurrency as an asset class by investigating the trading performance and behaviour of crypto traders. The findings that I present help traders identify and mitigate behavioural biases, which constitute a significant risk factor, as well as make more informed trading decisions.

Specifically, the first behavioural bias I investigate is the disposition effect. By learning to account for this bias, traders may benefit by optimising their tax costs on realised gains and losses Dhar & Zhu (2006).

The second bias that I investigate shines the light on retail cryptocurrency traders exhibit signs of the gambler's fallacy. As such, traders may try to learn to avoid relying on trend-seeking strategies and instead aim to research the fundamentals of the projects that are driving innovations in the crypto space.

Finally, the findings of the third analysis on the impact of market sentiment on trader performance is of interest not only to traders, but to regulators as well. This is due to the increasing popularity and association between prominent business figures (on social media platforms) and major cryptocurrency coins, which can result in herd behaviour and potentially detrimental results to traders who simply jump and act swiftly on the opinions of others who do not share their risk tolerance.

The contributions of this thesis provide insight into the behaviours of crypto traders and the characteristics of this novel asset class.

Chapter 2

Disposition Effect in Cryptocurrency Markets

Chapter 2

Disposition Effect in Cryptocurrency Markets

2.1 Introduction

The disposition effect is a well-documented behavioural bias that is defined as the tendency of an individual to realise their gains while holding on to their losses (Shefrin & Statman 1985). Since this seminal work, many researchers have aimed to estimate this bias and how it impacts performance (Odean 1998, Wegener & Petty 1995, Grinblatt & Keloharju 2001). In general, these studies have shown significant evidence of the disposition effect and have found that this bias negatively impacts performance. While these papers have focused on measuring the disposition effect in the context of traditional financial markets, our understanding of this bias in the cryptocurrency field remains limited.

The cryptocurrency market has attracted hundreds of thousands of retail investors, partly due to the technological innovation of being an anonymised payment system, and perhaps even more so due to the extreme returns witnessed by this market, which greatly surpass those reported in traditional markets. Given that the crypto market embraces unique characteristics, such as complete anonymity, decentralisation, returns and high volatility (Baur et al. 2018, Bianchi 2020, Hu et al. 2019, Liu & Tsyvinski 2021), I aim to investigate whether traders exhibit the disposition bias and quickly realise returns, or are likely to hold on to their investments over the long run as the industry propagates forward through significant changes that are constantly shaping this novel asset class.

In order to do so, I use a unique proprietary data set of individual cryptocurrency traders from an anonymous exchange.

I adopt a popular method developed by Odean (1998), called the disposition spread, that measures the tendency of an individual to realise a gain relative to a loss, and find evidence of anti-disposition effect among cryptocurrency traders. Specifically, I find that this effect is pronounced when calculating the disposition spread on weekly, monthly and quarterly frequencies. The results show that on average the disposition spread – the difference between the proportion of gains realised (PGR), calculated as the ratio of realised gains to realised plus unrealised gains, and the proportion of losses realised (PLR), calculated as the ratio of realised losses to realised and unrealised losses, – is negative. Thus there is evidence of an anti-disposition effect in the crypto market. This anti-disposition effect is prominent for traders in age groups of up to 50 years old and decreases thereafter. So traders, especially the younger ones, are more prepared to hold onto their winning positions in this market. There is also an element of learning and experience, as older traders tend to behave in a less biased fashion, consistent with much of the behavioural finance literature. Overall, my results show very different behaviour of investors in the cryptocurrency space, than those in traditional financial markets, for example in FX, equity and real estate markets.

The key contribution of this paper is to shed light on the disposition effect among cryptocurrency traders. My findings are of interest to a wide range of audiences, including those wishing to understand crypto price dynamics and traders themselves who may want to better understand their own behaviour and thus improve their performance. Regulators may be able to use my conclusions in order to guide and protect new investors in this market and academics may expand on my findings to better explain the performance of cryptocurrency traders relative to those in other markets.

The remainder of this paper is organised as follows. Section 2.2 describes the theoretical literature on the disposition effect in general, as well as empirical studies on this bias in traditional markets. Section 2.3 presents the methodology adopted in this paper. Section 2.4 outlines the data set used as well as some descriptive statistics. Section 2.5 presents the results and discusses the findings. Finally, Section 2.6 concludes this paper.

2.2 Literature Review

2.2.1 Theoretical Studies

According to Shefrin & Statman (1985), the disposition effect has its roots in mental accounting, regret aversion and problems with self-control and there might be a connection between the disposition effect and the prospect theory. Prospect theory, which was developed by Kahneman (1979), states that decisions are based on the potential values of gains and losses and not on the final outcome; gains and losses are ordered according to a certain heuristic. Furthermore, they are compared to a certain reference point and not in absolute terms. If prices rise, investors, who rely on the original purchasing price can see this as a sure gain if the asset is to be sold versus a risky decision to hold this asset. If prices fall, holding an asset is considered as an investor leaning towards risk, while selling it would be a sure loss.

There is a common agreement in the academic research that the effects of the reference point, which Kahneman & Riepe (1998) are calling cognitive illusions, are mistakes that are not easy to eliminate. In this paper it is proposed to have a more systematic analysis of market conditions. According to Wegener & Petty (1995), the way to correct the error in social judgement is to better understand the circumstances. When an investor can fully understand his or her affinity towards holding on to losing assets, he or she could better grasp the outcomes of the actions over time, which helps him or her to change the behaviour. Dhar & Zhu (2006), Feng & Seasholes (2005) and Grinblatt & Keloharju (2001) ask whether an investor's level of learning is responsible for the tendency to keep losers and show that more sophisticated investors with more information tend to keep the losing assets less. So, overall, the more experienced the investor, the weaker the disposition effect.

Dhar & Zhu (2006) show that wealthier market participants and participants employed in professional occupations, as well as those who trade more frequently, tend to show a lower susceptibility to the disposition effect. This means that investors are able to learn to adjust for the disposition effect.

According to Hayley et al (2019), the disposition effect limits upside volatility, resulting in a negative skewness of the probability density function of the realised profit and losses of market agents. Using a dynamic panel quantile regression model and the unique characteristics of the FX market, a new measure of disposition effect is introduced. The method to measure and model this behavioural bias proposed by Hayley et al (2019) could be applied to other asset classes, i.e. digital assets (cryptocurrencies and tokens).

The disposition effect can be seen across different traditional and alternative asset classes. Hayley & Marsh (2016) describe behaviour in foreign exchange, and Shefrin & Statman (1985) in equities. According to Genesove & Mayer (2001), there is a presence of the disposition effect in the real estate market, and Crane & Hartzell (2010) found the disposition effect in the actions of investment professionals, managing REITs, and this disposition effect cannot be explained by tax optimisation, asymmetric information or other considerations.

There is a branch of literature that shows the importance of accounting for an adaptive reference point when estimating the disposition effect (Chiyachantana & Yang 2013, Kőszegi & Rabin 2006, Arkes et al. 2008, Shi et al. 2015). Overall both theoretical and experimental studies show that traders update the reference point against which they compute gains and losses over time. Generally, investors move the reference point in the direction of newer, recent prices and newer, realised outcomes. Odean (1998) argues that even though the purchase price plays an important role in determining the reference price, it may only be one of the factors that determines the latter. Moreover, Chiyachantana & Yang (2013) argue that while several researchers adopt the initial purchase price as a fixed reference point, others, such as Kahneman (1979) and Thaler & Johnson (1990) show that the reference price is likely to be dynamic and may shift from the purchase price in response to changes in the characteristics of the asset. Barber et al. (2007) also mention the importance of incorporating of an adaptive reference point.

Studies, such as Chiyachantana & Yang (2013), Arkes et al. (2008), Shi et al. (2015) and Kőszegi & Rabin (2006) show that outcomes and gains/losses significantly influence risk taking decision and the disposition effect.

To illustrate, if crypto asset A was bought when the price was £100, and then dropped to £90 or went up to £110, then the reference point would be adjusted downwards or upwards respectively. Furthermore, a large price change can affect the individuals' willingness to adjust the reference point to the new price level, which such willingness is larger for smaller losses.

For example, an investor who purchases crypto asset B for £100, which drops to £99 shortly after, is more likely to adjust the reference price to the new price, compared to investor, who purchases the same asset at the same price; however, with the price, dropping significantly to £50. Hence, the willingness to adjust the reference price based on changes in the market can subsequently affect the estimation of the disposition effect.

After taking into consideration the behavioural finance literature, previous research regarding the disposition effect and the development of digital assets, my goal is to shed light on the existence of the disposition effect in the cryptocurrency markets. How do cryptocurrency investors really behave? Do they behave similarly to investors in other markets? If not, what are the implications?

2.2.2 Empirical Studies

According to multiple studies, there is a presence of the disposition effect in global financial markets. Odean (1998), who analysed 10,000 traders at a large US brokerage house, finds that it is 1.5 times more probable to realise gains than to realise losses. These results are consistent with the study of Weber & Camerer (1998) who also showed that gains are 50% more likely to be realised than losses. Feng & Seasholes (2005), Chen et al. (2007) and Grinblatt & Keloharju (2001) analysed markets in different geographies – Europe and Asia – and find results that support those of Odean (1998).

Chen et al. (2007), Dhar & Zhu (2006), Feng & Seasholes (2005), Nolte (2012), Richards et al. (2017) researched the connection between the disposition effect and the individual characteristics of market participants, such as experience, wealth, investor sophistication, experience and the use of automated trading systems. There are multiple proxies for investor sophistication, for example level of income and wealth (Chen et al. 2007, Dhar & Zhu 2006, Seru et al. 2010), professional occupation (Grinblatt & Keloharju 2001, Shapira & Venezia 2001) and the degree of how diversified portfolios are (Feng & Seasholes 2005). Overall, the authors find that the more sophisticated an investor is, the less pronounced the disposition effect is. Grinblatt & Keloharju (2001) analyse the Finnish stock market and discover that financial and insurance institutions exhibit less disposition effect than less sophisticated investors, such as households, general government and non-profit organisations. Feng & Seasholes (2005) find that the most sophisticated investors show a reduced sensitivity to selling losing investments of at least 67%. Moreover, Dhar & Zhu (2006) point out that the disposition effect is more noticeable in the group of less experienced and less wealthy investors and less noticeable in the group of individuals employed in professional occupations. Finally, Calvet et al. (2009) analyse households in Sweden and find that individuals are more likely to sell winning stocks, but this tendency is weaker for wealthier investors with diversified portfolios of stocks and stronger for households, who tend to sell stocks that have increased in value.

Generally, the disposition effect is more pronounced with novice and less experienced investors. Feng & Seasholes (2005) apply a methodology, where they use the number of positions a trader has taken as a degree of sophistication. They found that investor sophistication and trading experience eliminate the disposition effect over time, as investors gain experience. Seru et al. (2010) support the result above that the disposition effect declines as traders trade more in terms of cumulative number of trades, but the relationship becomes weaker when experience is measured in years. Chen et al. (2007) conducted a study using Chinese data and found similar results to those for the US and conclude that there is a disposition effect, and that it declines with experience. Overall, investors learn through experience to eliminate or adjust for the disposition effect.

Several researchers investigated the relationship between the disposition effect and automated trading systems. Linnainmaa (2010) analyses behaviour of individual traders in Finland and explains poor performance and the disposition effect by the use of limit orders, especially sell limit orders placed above the purchase price of the asset, which realise gains, cap upside and add to the disposition effect. Nolte (2012) agrees with above that take-profit orders add to the disposition effect for small trades in the foreign exchange market. He also mentions the inverted disposition effect for trades with small gains and losses, which is caused by investors closing their positions with stop loss orders and by using take-profit strategies. Richards et al. (2017) focus on the UK stock market and individual investors and use hazard models to analyse the effect of stop loss orders on the disposition effect. In this study, market participants that use stop loss orders are less likely to realise gains of stocks that appreciate. In addition, these traders with stop loss orders are more likely to sell stocks at a loss, relative to others. Hence, traders that use stop losses exhibit a lower disposition effect.

2.3 Methodology

2.3.1 Calculating Trader Profits and Returns

Profit is defined as a change of the balances taken into account any fund inflows and outflows.

Similar to Gemayel & Preda (2021), I decompose profit into realised and unrealised components in order to analyse the performance of traders. This methodology allows us to better understand the sources of traders' profit and losses. Realised PnL represents the results of active portfolio management that captures the returns associated with increase or decrease of quantities of assets held; unrealised PnL represents the returns from the passive holding of a portfolio.

In our case of an anonymous crypto exchange we have multiple crypto and fiat assets, which comprise the investment universe $\mathbb{M}$, and I will call them $m = 1, \ldots, M$. We also have multiple traders, called $n = 1, \ldots, N$. Finally, we have timestamps t.

Let each trader hold assets $Q^t_{m,n}$, defined as a vector of balances at time t, and denote a vector of prices at t against the base currency in time t by P^t_m. A vector of account debits/credits is $C^t_{m,n}$. Note that our base currency for all prices is USD.

The value of a balance in time t for a trader n for an asset m is then $P^t_m \times Q^t_{m,n}$. This follows from the balances in period $t-1$ $P^{t-1}_m \times Q^{t-1}_{m,n}$. Then I add any positional appreciation due to inventory balances $(P^t_m - P^{t-1}_m) \times Q^{t-1}_{m,n}$. Consequently, I add increases in the number of units of assets due to trading at time t: $(Q^t_{m,n} - Q^{t-1}_{m,n}) \times P^t_m$.

Finally, as PnL is defined as a change of balances minus net deposits, I should add all netted account debiting/crediting at time t, $C^{t-1}_{m,n} \times P^t_m$.

Overall, I get

$$\begin{aligned} P^t_m \times Q^t_{m,n} =& P^{t-1}_m \times Q^{t-1}_{m,n} + (P^t_m - P^{t-1}_m) \times Q^{t-1}_{m,n} \\ &+ (Q^t_{m,n} - Q^{t-1}_{m,n}) \times P^t_m + C^{t-1}_{m,n} \times P^t_m \end{aligned} \tag{2.1}$$

To calculate PnL, I go back again to the definition above that profit is the change in values of balances between two periods adjusted by the netted account debiting/crediting, so I get:

$$\begin{aligned} &P^t_m \times Q^t_{m,n} - P^{t-1}_m \times Q^{t-1}_{m,n} - C^{t-1}_{m,n} \times P^t_m \\ &\qquad =(P^t_m - P^{t-1}_m) \times Q^{t-1}_{m,n} + (Q^t_{m,n} - Q^{t-1}_{m,n}) \times P^t_m \end{aligned} \tag{2.2}$$

Then

$$Total\, PnL^t_{m,n} = (P^t_m - P^{t-1}_m) \times Q^{t-1}_{m,n} + (Q^t_{m,n} - Q^{t-1}_{m,n}) \times P^t_m \tag{2.3}$$

The first part $(P^t_m - P^{t-1}_m) \times Q^{t-1}_{m,n}$ is the unrealised component of profit, which shows the change in value of a passive holding of inventory. The second part $(Q^t_{m,n} -$

$Q^{t-1}_{m,n}) \times P^t_m$ is the realised trading component of profit, which reflects active trading causing changes in the number of units of inventory not related to cash in/outs. To make it more readable, I can rewrite it in the following way:

$$Unrealised\, PnL^t_{m,n} = \Delta P^t_m \times Q^{t-1}_{m,n} \tag{2.4}$$

$$Realised\, PnL^t_{m,n} = \Delta Q^t_{m,n} \times P^t_m. \tag{2.5}$$

The PnL is measured in USD and provides insight into the activity and behaviour of traders, especially when decomposed into unrealised and realised components. However, if market participants have different sizes of portfolios, I cannot compare dollar PnL in nomimal terms. As such, I also calculate the daily percentage change in PnL for all traders for all trading days as a measure of return on investment. The percentage PnL (which I further call $Returns$, as opposed to dollar PnL) are built for all of types of PnL above: unrealised, realised and total. These $Returns$ are calculated using time-weighted in and outflows and using division by the start value of each period.

2.3.2 Disposition Spread

I follow Odean (1998) and Barber et al. (2007) in characterising whether investors are subject to the disposition effect. For each investor I characterise, at a given frequency, gains and losses on each position and I also determine whether the position has been closed or is still open. From these data I can compute the proportion of gains realised and the proportion of losses realised.

Specifically, first paper gains and losses are calculated: PG_t^n and PL_t^n. Then, realised gains and losses: RG_t^n and RL_t^n are computed. Finally the proportions of gains realised and losses realised are calculated both in terms of USD amounts or number of trades.

In order to compute a gain or loss a reference price is required. In many empirical applications (Odean 1998) the entry price of the position is used as a reference. In others (Arkes et al. 2008, Chiyachantana & Yang 2013, Kőszegi & Rabin 2006, Shi et al. 2015), a more recent dynamically adjusted reference price is used. In this study, I take the latter approach and compute reference prices as recent prices at a variety of frequencies. So, for example, I might use as a reference price the most recent end-of-week value of the asset. I use weekly, monthly and quarterly reference prices below.

Generally, it is expected that computing the reference prices on a quarterly basis will give a higher probability that the position will be closed, realising a gain or a loss. Thus results will differ based on the chosen frequency.

For example, an investor buys two cryptocurrencies BTC and ETH each for £1,000. If both assets go up and he or she sells BTC on the same day, and ETH in 20 days, then on a weekly frequency, in week 1 there is 1 paper gain and 1 realised gain. Using a monthly frequency, there are 0 paper gains and 2 realised gains.

The final step is the calculation of the of proportion of gains realised (PGR) and the proportion of losses realised (PLR) over all traders and all periods:

According to Odean (1998),

$$PGR = \frac{RG_t^n}{RG_t^n + PG_t^n}$$

$$PLR = \frac{RL_t^n}{RL_t^n + PL_t^n}$$

and the disposition spread DS is defined as the proportion of gains realised (PGR) minus the proportion of losses realised (PLR). If market participants exhibit the disposition effect and tend to quicker realise gains, then this spread becomes positive.

But there is a question of how to aggregate and average these ratios across investors and time.

- **Dimension 1: Transaction vs individual level**

  Our **transactional level** analysis aggregates across gains and losses from all traders in a sampling period. Alternatively, **individual level** analysis calculates PGRs and PLRs, as well the disposition spread for each trader and each sampling period and subsequently averages across all traders/periods.

- **Dimension 2: US dollars vs counts**

  I calculate the components of the disposition spread, namely, PGs, RGs, PLs, RLs, in terms of both US dollars, as well as trade counts. Note that using counts places more emphasis on those traders with smaller portfolio sizes.

- **Dimension 3: Weekly vs monthly vs quarterly sampling frequencies**

  Calculations are based on weekly, monthly and quarterly frequencies. For example, for weekly frequency I calculate parameters per week. Reasoning: paper and realised gains/losses are depended on the window of observations. For example, it is less likely that a trader will sell an asset that they have purchased within the current week, which implies that the asset has a paper gain/loss, comparing to observing the same asset over a month, whereby a trader may be more likely to sell that asset.

I test the null hypothesis of the existence of the disposition effect, using the following one-tailed t-test: According to Odean (1998)[p. 1784];

$$t - statistic = \frac{(PLR - PGR) - 0}{\sqrt{\frac{PGR(1-PGR)}{RG+PG} + \frac{PLR(1-PLR)}{RL+PL}}}.$$

This test for significance takes into account each PG, PL, RG and RL as separate independent observations, summing them over all investors. This absence of independence will cause an inflated t-statistic, but it will still not bias PLR and PGR. According to Odean (1998), if this t-statistic is large enough, some lack of independence is not problematic. But if a t-statistic is not far from the critical threshold of significance, results should be analysed carefully[1]

[1]The first analysis (no clustering) counts each sale for a gain, sale for a loss, paper gain on the day of a sale, and paper loss on the day of a sale as separate independent observations. Subsequently, these observations are summed across investors. This assumption of independence across observations does not hold perfectly. For Instance, consider an investor who chooses not

The Disposition Spread (DS) is the difference between the Proportion of Gains Realised (PGR) and the Proportion of Losses Realised (PLR). This means that the hypotheses for the disposition effect based on the DS are:

HA: $PGR > PLR$

H0: $PGR <= PLR$

Thus, given these one-sided hypotheses, the appropriate test to use is a single-sided t-test, which is also what is used in the literature (Odean 1998). I have mentioned that in the methodology in Section 2.3.

According to Odean (1998), an alternative method to calculate the disposition spread can be used by making different independence assumptions. Instead of the assumption that independence exists at the trade level, now it is assumed that it only exists at the investor level. So, there is a possible relationship between the PGR and PLR within the investor's crypto wallet, but not across crypto wallets. The PGR and PLR are calculated for each investor for each trading period, and then the difference is built for the calculation for the disposition spread. I then average the DS for each trader across all the trading periods to get the DS for each investor separately. PGR and PLR for each investor-period are defined as:

to sell the same asset on repeated occasions. Hence, it is likely that the decision not to sell on one day is not independent of the decision not to sell on another day. Conversely, two traders may be motivated to sell the same asset on the same day given some common information that they receive.. This lack of independence will inflate the test statistics; however it would not bias the observed proportions (Odean 1998). Thus, the alternative analysis that clusters transactions per trader takes into account potential dependence between trading decisions of a particular trader. This method is comparable to including trader fixed effects in a regression model to control for trader-specific effects.

$$PGR_t^n = \frac{RG_t^n}{RG_t^n + PG_t^n}$$

$$PLR_t^n = \frac{RL_t^n}{RL_t^n + PL_t^n}.$$

The first methodology of obtaining PGR and PLR weights each investor by the number of realised paper gains and losses, while the second alternative methodology weights each investor wallet equally. The second methodology ignores that more active investors with more trades have more accurate estimates of their true PGR and PLR.

According to Odean (1998), the disposition spread has the disadvantage that it is not suitable for cross-sectional comparisons because of the mechanical relationship between the size of the portfolio and the disposition spread. For example, let us have two investors with the similarly pronounced disposition effect. The difference is only that an institutional investor I has 1000 assets and a retail investor R has 40 assets. Let us assume half of assets went up, half down, and both sell 75% of winners and 25% of losers. Investor I sells 0.75*0.5*1000 = 375 winners and 0.25*0.5*1000 = 125 losers. PGR is 375/(375+500) = 0.4285, PLR is 125/(375+500) = 0.2. Investor R sells 0.75*0.5*40 = 15 winners and 0.25*0.5*40 = 5 losers. PGR is 15/(15+20)=0.4285, PLR is 5/(5+20) = 0.2. The DS are the same for both investors.

Now assume that both investors only sell 15 winners and 5 losers. Investor I sells 15 winners and 5 losers. PGR is 15/(15+500) = 0.02913, PLR is 5/(5+500) = 0.0099. Investor R sells 15 winners and 5 losers. PGR is 15/(15+20)=0.4285, PLR is 5/(5+20) = 0.2. Then the DS of investor I is much less than the DS of investor R.

This is why some researchers, e.g. Cici (2012), advocate using the disposition ratio, DR, defined as PGR/PLR.

2.4 Data

The data for this paper comes from an anonymous crypto exchange, which I call ExchangeX, and covers over 1.5 million trades executed by over 15,000 traders over the period from June 2017 to December 2018. Trading is done in spot cryptocurrency markets; there are no leveraged trades and also no trades with derivatives - such as futures and options on crypto assets in this data set. Each trade contains the following information: ID of the trade, timestamp, trader ID, asset pair, direction, volume and opposite volume and executed price. Users can place both market orders and limit orders that enter the order book, and these are matched via a matching engine; however, the data set does not allow us to identify and differentiate between these orders. Demographic information is also recorded, including the age of the trader as well as the geographical location. Panel A in Table 2.1 presents some descriptive statistics.

The age of the accounts in the data set offers significant insights into the behaviour and life cycle of these accounts. Most notably, the fact that the median age is only 27 days highlights that a majority of these accounts have a short lifespan, with half of them lasting less than a month. The minimum age of just one day might imply that there are accounts being created and potentially abandoned or closed within a day. This could be indicative of trial users, spammers, or even users who are dissatisfied with the service or platform. Alternatively, a surge in marketing campaigns or promotions could result in a spike in new account creations. However, if these users do not find long-term value, they might abandon the account soon after. It is also interesting to note the disparity between the mean age of 101 days and the median of 27 days. This suggests that while there are many accounts that have a short lifespan, there are also a considerable number of accounts that last much longer, potentially skewing the average upwards.

The age data for traders ranges from 20 to 71 years, showcasing the platform's appeal to both young adults and older individuals. The majority of traders are in their mid-thirties, suggesting they might be focused on financial growth and diversifying their investments. Younger traders, in their late twenties and early thirties, could be tech-savvy and open to modern trading tools. On the other hand, those above 40, reaching up to 71, might prefer more conservative and long-term investment strategies, seeking stability and safety.

Figure 2.1 shows distribution of age categories of traders on ExchangeX, and the age of the majority of traders lies between the ages of 20 and 50. Figure 2.2 shows age distribution of traders, and traders aged 20 to 50 are the most frequent; however, the last category still has around 1'000 traders. We can also see in Figure 2.3 the box plot of age across countries, where countries are shown with more than 30 traders; this is done for display purposes. Generally, for most countries, the body of the plot tend to be between the ages of 25 and 45 years.

Outliers can be detected in various ways. One common method is to use the Interquartile Range (IQR). Any data point below Q1 - 1.5 * IQR or above Q3 + 1.5 * IQR is considered an outlier.

When analysing the number of assets traded by individuals on the platform, it becomes evident that the diversification among most traders is rather limited. A significant majority of traders primarily engage with only 2 or 3 crypto assets.

This concentration suggests that while the crypto market may offer a plethora of asset options, many traders either prefer to stay within the confines of what they know or are possibly swayed by the popularity of certain assets. Such a trend might be influenced by various factors including information asymmetry, where traders feel more confident investing in well-known assets due to abundant information and perceived lower risks. Alternatively, it could also reflect a general resistance to diversify in a volatile market like cryptocurrency, where familiarity with specific assets might provide a semblance of predictability or control. However, on the other end of the spectrum, a very small fraction of traders seem to fully exploit the diversity of the crypto market, trading up to 65 different assets. These traders might be more risk-tolerant, better informed, or might be employing strategies that involve diversification to optimise returns and hedge risks. This dichotomy between the majority and the outliers underscores the importance of trader education and the potential benefits of diversification in cryptocurrency trading.

Figure 2.8 shows distribution of unique number of assets traded, while Figure 2.9 shows the box plot of unique number of assets traded by country, where Switzerland and UK are the countries with the highest range.

Regarding the number of trades executed by traders, over half of the traders, denoted by a median of 19 trades, lean towards a reserved trading frequency, perhaps driven by risk aversion, limited available capital, a preference for a passive, long-term investment strategy, or potential gaps in trading knowledge and confidence. This suggests that a significant portion of the platform's user base might be better served with educational resources, tools for conservative investment strategies, and confidence-boosting informational support. In stark contrast, another subset of traders exhibits an extraordinarily high trading frequency, with as many as 50,871 trades. Such high trading activity can be attributed to algorithmic traders using pre-set criteria to execute trades rapidly, day traders capitalising on minor price fluctuations, institutional investors managing vast capital, or adept professional traders navigating the market's nuances.

Figure 2.6 shows distribution of total number of trades; the number of trades lies between the ages of 8 and 29. Figure 2.7 shows the number of trades per country.

The size of trades executed on the platform showcases a significant variance, ranging from the modest sum of $1 to a substantial amount of $620,021. This expansive range underscores a remarkable diversity in trading behaviours and potentially the financial capacities of the platform's user base. A closer examination of the average trade size reveals it to be $489, but this number is not entirely representative of the typical trader's activity. The median trade size, which stands at $201, paints a more accurate picture of the central tendency and indicates that a majority of trades are of a more modest scale. This difference between the mean and median emphasises the influence of outlier trades, which considerably skew the average upwards. These outliers could be attributed to a limited number of trades by institutional investors or high-net-worth individuals who engage in large-volume trades. Their presence amidst a predominantly retail-focused user base might indicate that the platform caters to, or is gaining traction among, professional traders or entities with significant capital. Such a juxtaposition can present both opportunities and challenges. On one hand, larger trades contribute significantly to the platform's liquidity. On the other, these larger traders may have monopolistic influence over the dynamics of pricing on the exchange, thus impacting the performance of smaller retail traders.

Figure 2.4 shows distribution of age categories of traders on ExchangeX, where most trades are between \$14 and \$409. Figure 2.5 shows the box plot of average trade size per country. In general, three is no large differences among the distributions of trade size among most countries. Some of the richer countries, such as Hong Kong, Singapore and Korea, have higher on average trade size. Other countries, such as Ukraine and Philippines, tend to have smaller trade sizes.

Next, I calculate and decompose USD PnLs as described in the previous section. Further, I then scale to as to compute percentage PnLs or returns.

The descriptive stats of the calculated returns, called $Return_{Unrealised}$, $Return_{Realised}$ and $Return_{Total}$ can be seen in Panel B of Table 2.1.

The results are extremely interesting. The average return on inventory $Return_{Unrealised}$ has been significantly positive with a mean of 0.20%. The total return $Return_{Total}$ is on average positive too with a mean of 0.11%. Unrealised PnLs are reported on the total number of days when a trader had positive value in the account. Realised PnLs are reported on the basis of those days, when there were actual trades. Interestingly, the realised component of PnLs $Return_{Realised}$ has been negative with an average of a mean of -0.75% and median of -0.45%, that tells us that on average market participants tend to buy at a premium to the subsequent reference price and sell at a discount to that price.

2.5 Results

The results for the transaction level are shown in Table 2.2. First, the results for negative and positive realised profits are reported separately on weekly, monthly and quarterly frequencies. Then, similarly, the results for paper profits - gains and losses separately - are presented. When PGR and PLR metrics are calculated on a weekly basis and on US dollar values, PGR of 0.018 is larger than PLR of 0.0179, which indicates the presence of a positive, however economically small disposition effect. When these ratios are calculated on a monthly and then on a quarterly bases, $PLRs$ are larger than $PGRs$, so I obtain what can be called the anti-disposition effect (when traders tend to be quicker to realise losses) with the values of PGR of 0.0119 and PLR of 0.0138 if calculated on a monthly basis and 0.0131 and 0.0156 if on a quarterly basis. In the more recent paper (Barber et al. 2007), where they research equity markets in Taiwan, the results for PGR and PLR are the same order of magnitude (PGR values obtained by Odean in the range from 0.0345 to 0.0439, PLR values from 0.0147 to 0.0165 for individual investors in equity Taiwanese market from 1995 to 1999), as I obtain in this paper.

When both ratios are calculated on a quarterly basis, it would make them more comparable to studies of the disposition effect, which often also use quarterly frequencies[2]. The calculation of PGR and PLR shows that in both cases, based on both US dollar amounts and on counts, PGR is smaller than PLR, which demonstrates the strongly pronounced anti-disposition effect. The calculated t-

[2]Note that some studies in equity markets use Odean's original method, that does not take into account the adaptive reference method which I have incorporated into the study

statistics in both cases are very large, which means that the results are significant. The disposition ratio is 0.854 when calculated on a US dollar basis and 0.799 when calculated on a count basis.

The results based on a monthly basis are the following: the disposition spread is negative in both cases based on counts and on US dollar values; the t-statistics are significant again. The disposition ratios are 0.860 and 0.822, which again shows the absence of the disposition effect. This means that market participants in cryptocurrency markets tend to delay the realisation of gains and stick to winning positions. The negative disposition effect found in the cryptocurrency markets contrasts with what others have found in equity, fiat currencies and real estate markets.

Next, I calculate the metrics, proportions and ratios, described in the methodology section, using grouping both by trade date and by wallet ID and by calculating the ratios for each wallet separately. The results can be seen in Table 2.3. Again, I calculate separately negative profits (and counts) and positive profits (and counts). PGR proportions are 0.018, 0.026 and 0.036 for weekly, monthly and quarterly frequencies, when calculating on a currency basis; PLR values are 0.023, 0.038 and 0.054. By building the differences and ratios, this gives me the DS values of -0.0053, -0.0112 and -0.0178, which again indicates a negative, however economically small disposition effect.

When applying the above described methodology on counts, I also obtain negative values for the disposition spread DS for all sampling frequencies: -0.0048, -0.0078 and -0.0115. Regarding the t-statistics, these are significant for monthly and quarterly basis for calculations based on US dollar basis and not significant for weekly and for results on a count basis.

Overall, the results for both individual and transaction level results show us the presence of the negative disposition effect.

2.5.1 Sub-samples based on Pre and Post Market Peak

In order to test whether traders exhibit the disposition effect differently during a bull market and a bear market, I recalculate the inputs for, as well as the DS and DR metrics for the pre-peak market period (from June 2017 to January 2018) and the post-peak period (January 2018 to Demceber 2018) separately. This is repeated based on the transaction level approach as well as with trader clustering; however, I only present the results for the former analysis in Table 2.4 as the results obtained with trader clustering are very similar.

In general, I report values for the DS and DR measures that are very similar between the bull and bear market periods, and thus similar to the results reported for the overall sample. This means that the crypto traders in my sample do not alter their behaviour with respect to realising gains and losses based on market trends. In other words, the disposition effect is a behavioural bias that is innate to the trader and is not impacted by exogenous factors such as market trends.

2.5.2 Sub-samples based on Minimum Number and Dollar Value of Trades

As a robustness test, I recalculate the transaction-level and individual level disposition effect by restricting the sample to only those who have executed a minimum number of trades or a minimum dollar value of trades[3]. The results for the transaction-level and individual-level analyses based on minimum number of trades executed are presented in Table 2.5 and Table 2.6, respectively.

In general, the results and conclusions are consistent with those obtained when using the full sample, and thus further support the earlier finding of the presence of a negative disposition effect among crypto traders on the exchange.

2.5.3 Sub-samples based on Average Trade Dollar Value

In this analysis, I investigate whether traders with different average trade sizes exhibit different disposition effects. The motivation is that if the most active traders are the most experienced, then these individuals may exhibit a lower disposition effect (Frino et al. 2015).

In order to do so, I divide the sample into smaller sub-samples or quintiles based on the average dollar value of traders' transactions, whereby Q_1 represents the quintile with traders that have the smallest average trade size, and Q_5 represents

[3]The analyses based on the minimum dollar value are not reported as they are very similar to those from the analyses based on the minimum trade count. Note that the thresholds used for the minimum average dollar value of trades are based on the descriptive statistics of the overall sample as shown in Table 2.1, and include \$20, \$200, and \$400

the quintile with traders that have the largest average trade size. The DS and DR are then calculated for each quintile separately. I repeat the analysis based on the transactional-level approach as well as using individual-level clustering; however, I only report the results for the former in Table 2.7 as the conclusions are similar.

In general, the results in Panel A based on dollar value of trades show that traders in the lower quintiles Q_1, Q_2, and Q_3 have a slightly positive disposition spread, while those in Q_4 and Q_5 have a slightly negative disposition spread. This may be an indication that those with a higher number of trades, and thus more experience trading, are likely to have a lower disposition effect as they avoid early realisation of gains and set stop limits to their losses. However, this difference is very small. Moreover, when we look at the results based on the trade count as shown in Panel B of Table 2.7, we see that all quintiles exhibit a negative disposition spread.

Thus, the findings from this analysis suggest that there is no significant difference in the disposition effect among traders who trade less (i.e. less experienced traders) and those who are more seasoned. In other words, experience through trading does not reduce the disposition effect.

2.5.4 Disaggregation of Market Participants by Age

The observed anti-disposition effect is a very interesting and a thought-provoking finding and may offer important implications. The logical question arises whether different types of market participants exhibit different levels of this behaviour. As described in the literature review section above, the disposition effect is ceteris paribus less pronounced with experienced and older, more professional traders with higher levels of education and wealth. I conduct further analysis, where I divide the data into 5 age categories or subsets, and I repeat the above described methodology based on no trader clustering and also with trader clustering.

The 5 trader age categories are: (18.0, 30.0], (30.0, 40.0], (40.0, 50.0], (50.0, 60.0], (60.0, 75.0].

The results of calculations of disposition spreads and disposition ratios at the transaction level for these age groups are presented in Table 2.4.

In Panel A the results are based on US dollar values, and disposition spreads for all 3 frequencies (weekly, monthly and quarterly) drop from a positive value to around zero, as age increases. Both at monthly and quarterly frequencies there is a clear indication of the negative disposition effect for all age groups for the transactional level, except the the first age group, when counted on US dollar basis.

In Panel B, where there are results on a count basis, we can see that the age groups from 18 to 50 exhibit a strong anti-disposition effect, while groups of traders who are from 60 to 75 years old have a less pronounced anti-disposition effect. Basing the calculation on counts (and not on US dollar values) has important implications, as in this case I weight each trader equally. My results suggest that younger individuals tend to exhibit a stronger level of this behavioural basis. The very youngest age group of traders - those who are from 18 to 30 years old - is the only group, when calculated on a dollar basis, that exhibit a positive disposition effect, which can be explained by quicker realisation of large positive gains.

Figure 2.14 shows box plots of the realised positive and negative profits of all trades, categorised by all age categories. Traders in the youngest age group of 18-30 have larger positive realised profits, then traders in other age groups, which pushes the measured disposition effect for them in the classical direction.

The results of distribution of the disposition effect can be shown in Figures 2.15, 2.16, 2.17 and 2.18. The results are the same for both methods and most traders have the disposition spread, which is symmetrically distributed around 0 with the disposition spread of most traders falling between mainly in the range between -0.1 and 0.1, regardless of whether the count or the dollar approach is used. One thing to highlight is that while there are some outliers in terms of the values obtained for the DS, these are due to the low number of transactions by these users and do not impact the overall conclusions as I conduct robustness checks to remove these outliers and obtain the same results. Moreover, several of the analyses I run explicitly apply a threshold for the minimum number of transactions, which eliminate these outliers from the respective analyses. Thus, the results I present throughout the paper are robust to outlier values in the disposition spread.

Box plots show countries with more than 5 traders. The analysis on the disposition effect per country shows that the disposition spreads revolve around zero, with some extremes, such as Switzerland, Turkey, Russia, Taiwan; however, these countries have higher number of observations, hence there are more extremes in these countries.

The results based on transaction level show significant disposition effect, however when I aggregate on individual level, I find that the disposition effect in general is not significant, when looking on trade counts, and only significant on a monthly and quarterly basis when looking on a dollar basis. This suggests that in the former analysis the results were biased towards those, who traded excessively; however, when all traders were weighted equally, we found that in general traders exhibit a much lesser anti-disposition effect.

Overall, traders exhibit the anti-disposition effect, that tends to be strongly articulated within age groups of up to 50 years old, and tend to decrease after; however I found an evidence of the positive disposition effect for the youngest traders on transactional level, based on US dollars. My results show different levels and direction of the disposition effect for traders in the cryptocurrency space, than those in traditional financial markets. Nevertheless, when I dig deeper and disaggregate traders into subsets, my results are similar to those of other researchers and suggest that traders learn, and the older they are, the less pronounced this behavioural bias is.

2.6 Conclusion

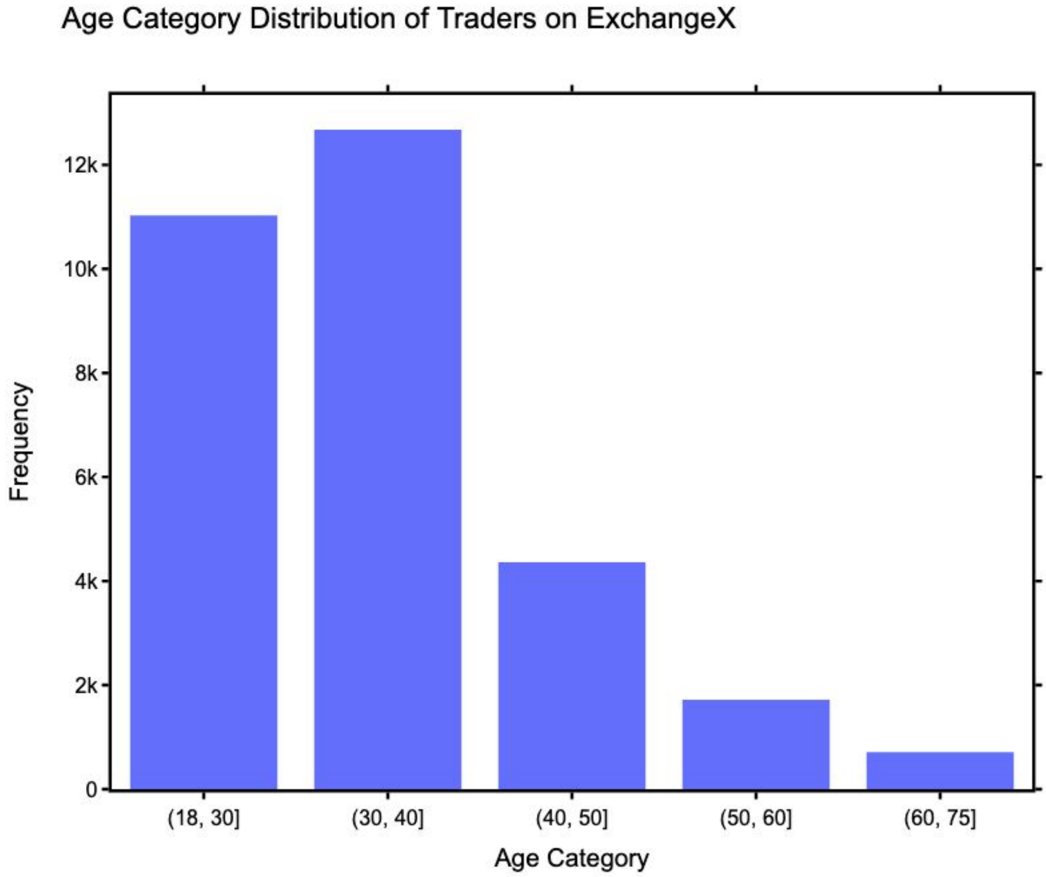
The majority of academic literature in the cryptocurrency space is related to Bitcoin and later also to Ethereum. A unique angle of this paper is the fact that I incorporate multiple different crypto assets and the real behaviour of thousands of market participants from June 2017 to December 2018.

Specifically, I investigate the disposition effect in cryptocurrency markets using a unique proprietary data set. I adopt a profit decomposition method in order to calculate performance, realised and unrealised profits and use these components to estimate the disposition effect using Odean's method. Overall, I find the presence of an anti-disposition effect. The study indicates that crypto traders' tendencies to sell winning or losing assets are consistent, unaffected by market conditions or trade size, suggesting that experience doesn't strongly influence investment biases. Age impacts behaviour, with traders under 30 showing a distinct tendency to realise gains more quickly, while older traders exhibit less of such biases. Overall, trading patterns suggest that the anti-disposition effect lessens with age, with cryptocurrency behaviours mirroring those in traditional markets.

The presence of an anti-disposition effect leads to two main points worth mentioning. First, the direction of the disposition effect in the cryptocurrency markets is the opposite to that in traditional financial markets. This means traders of crypto assets generally stick to winning positions. Second, there is an element of learning and positive experience, as older traders tend to behave more rationally, which is consistent with most of research in the behavioural finance literature.

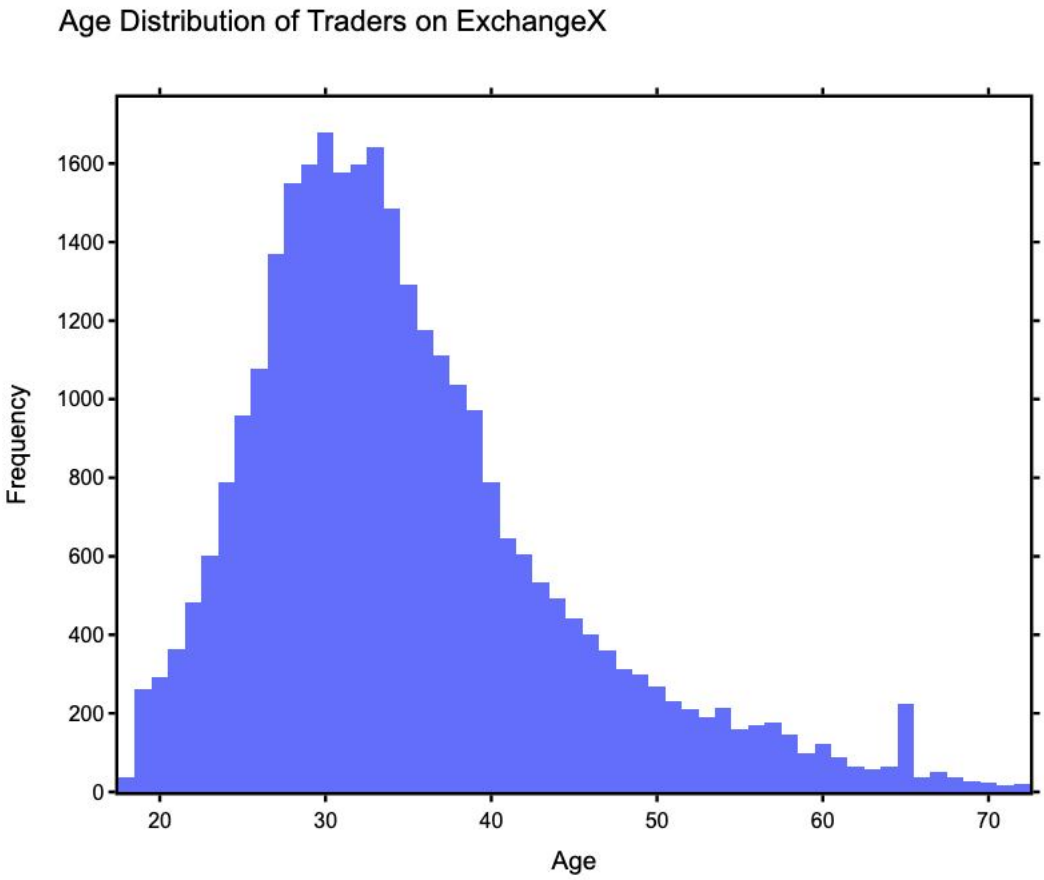
Finally, in the recent past, we have seen interesting cases, for example the case of GameStop, when young traders, driven by social media, push the prices in one direction, possibly very far from "fair" or "intrinsic" value. This shows us that accounting for the behavioural traits of this particular class of investors might be important in understanding short-run price dynamics both in stock markets and crypto markets.

Figure 2.1: Age Category Distribution of Traders



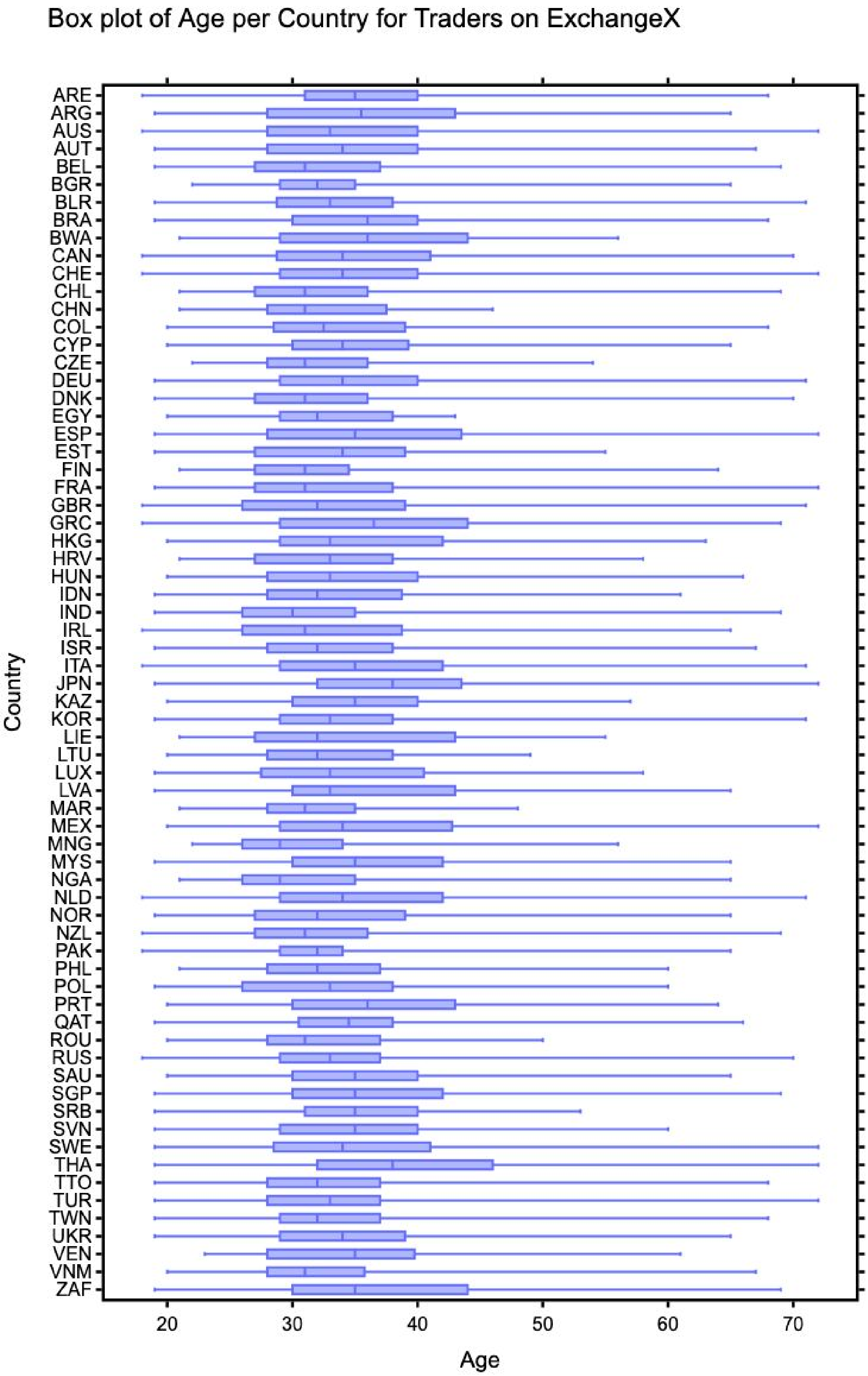
This figure shows distribution of traders on ExchangeX.

Figure 2.2: Age Category Distribution of Traders



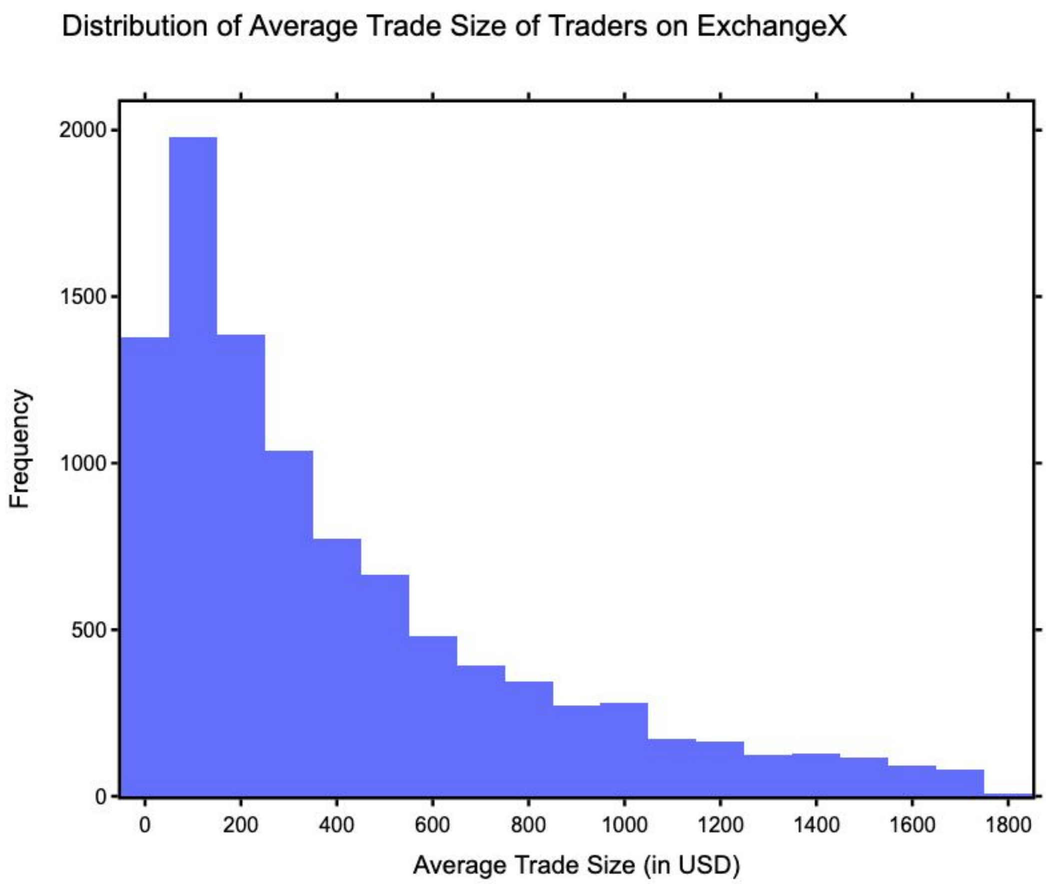
This figure shows distribution of traders on ExchangeX.

Figure 2.3: Box Plot of Age per Country for Traders on ExchangeX



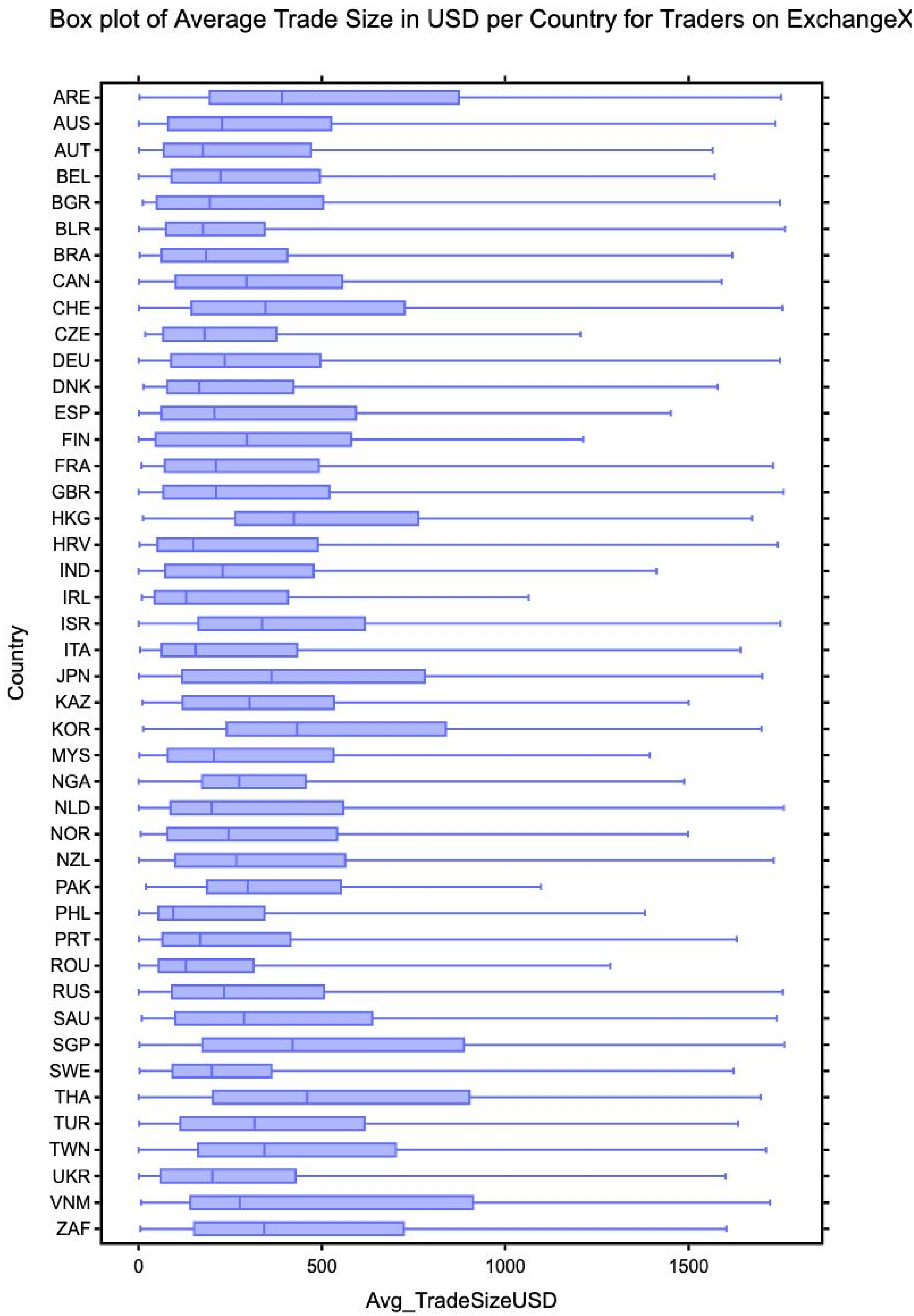
This figure shows box plot of age per country for traders on ExchangeX

Figure 2.4: Distribution of Average Trade Size of Traders on ExchangeX



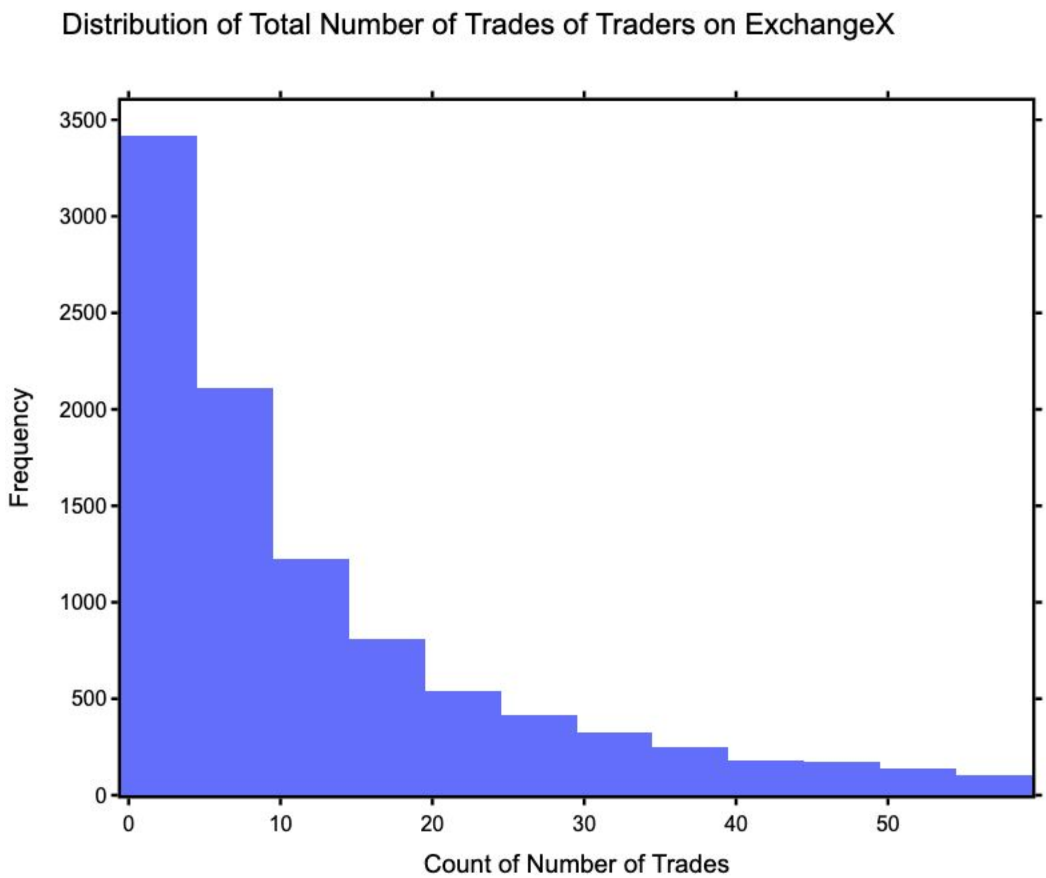
This figure shows distribution of average trade size of traders on ExchangeX.

Figure 2.5: Box Plot of Average Trade Size in USD per Country for Traders on ExchangeX



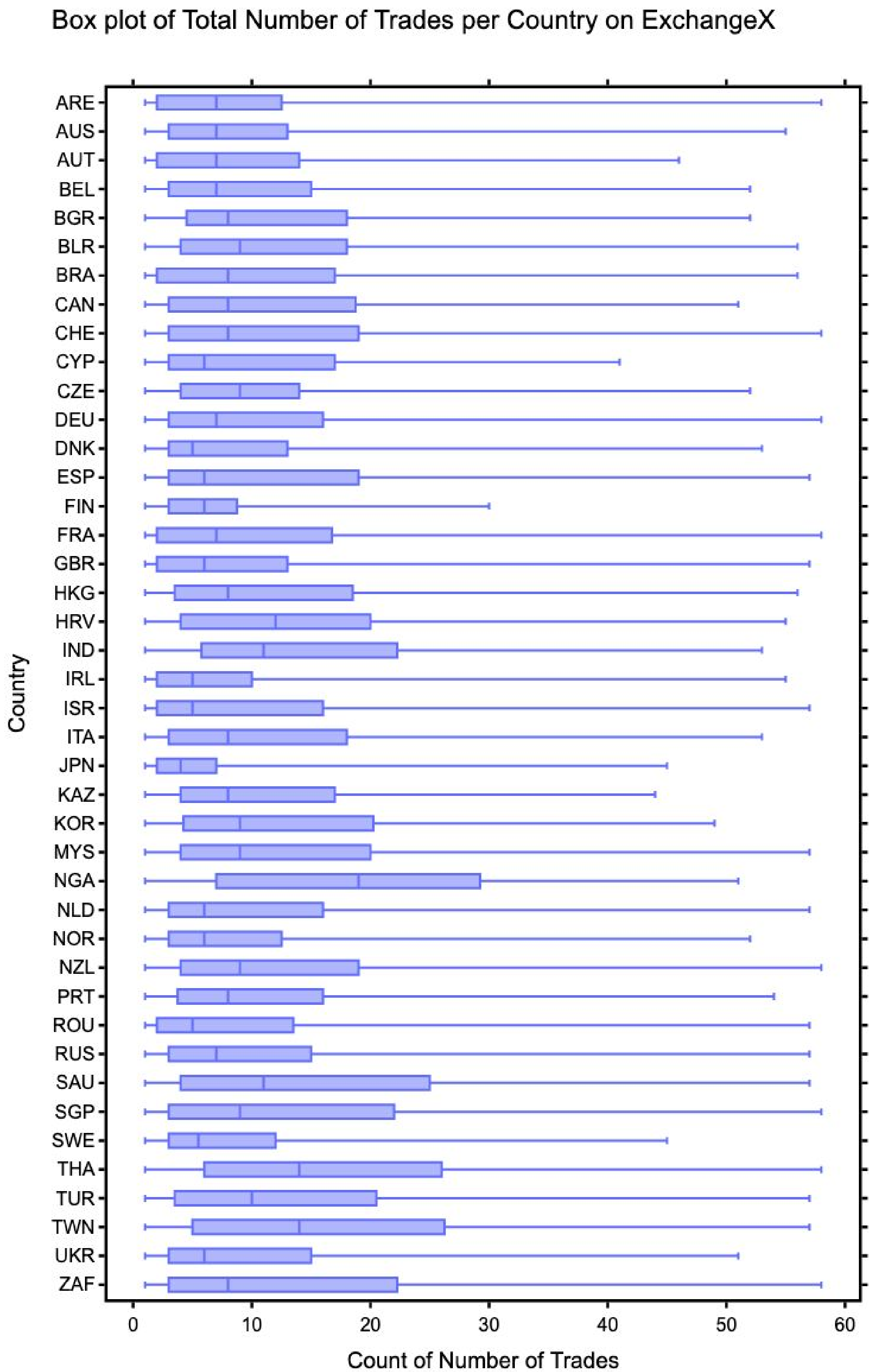
This figure shows box plot of average trade size in USD per country for traders on ExchangeX

Figure 2.6: Distribution of Total Number of Trades of Traders on ExchangeX



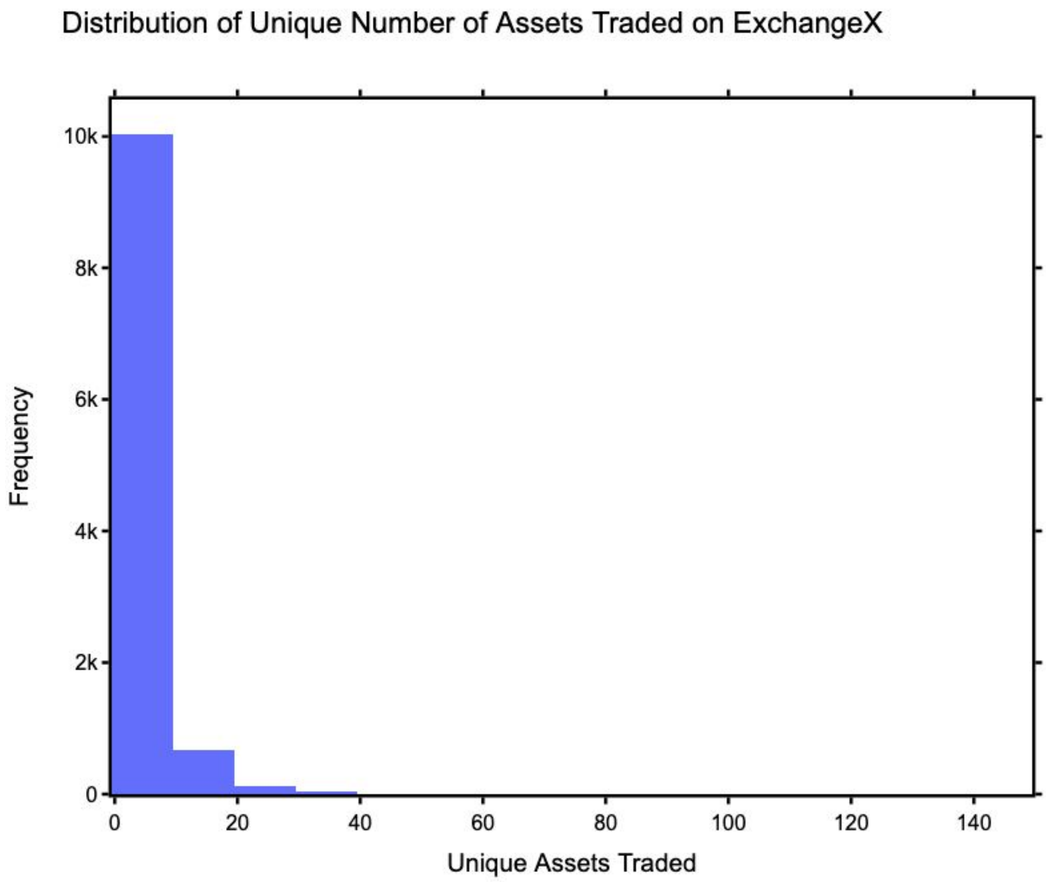
This figure shows distribution of total number of trades of traders on ExchangeX

Figure 2.7: Box Plot of Total Number of Trades per Country for Traders on ExchangeX



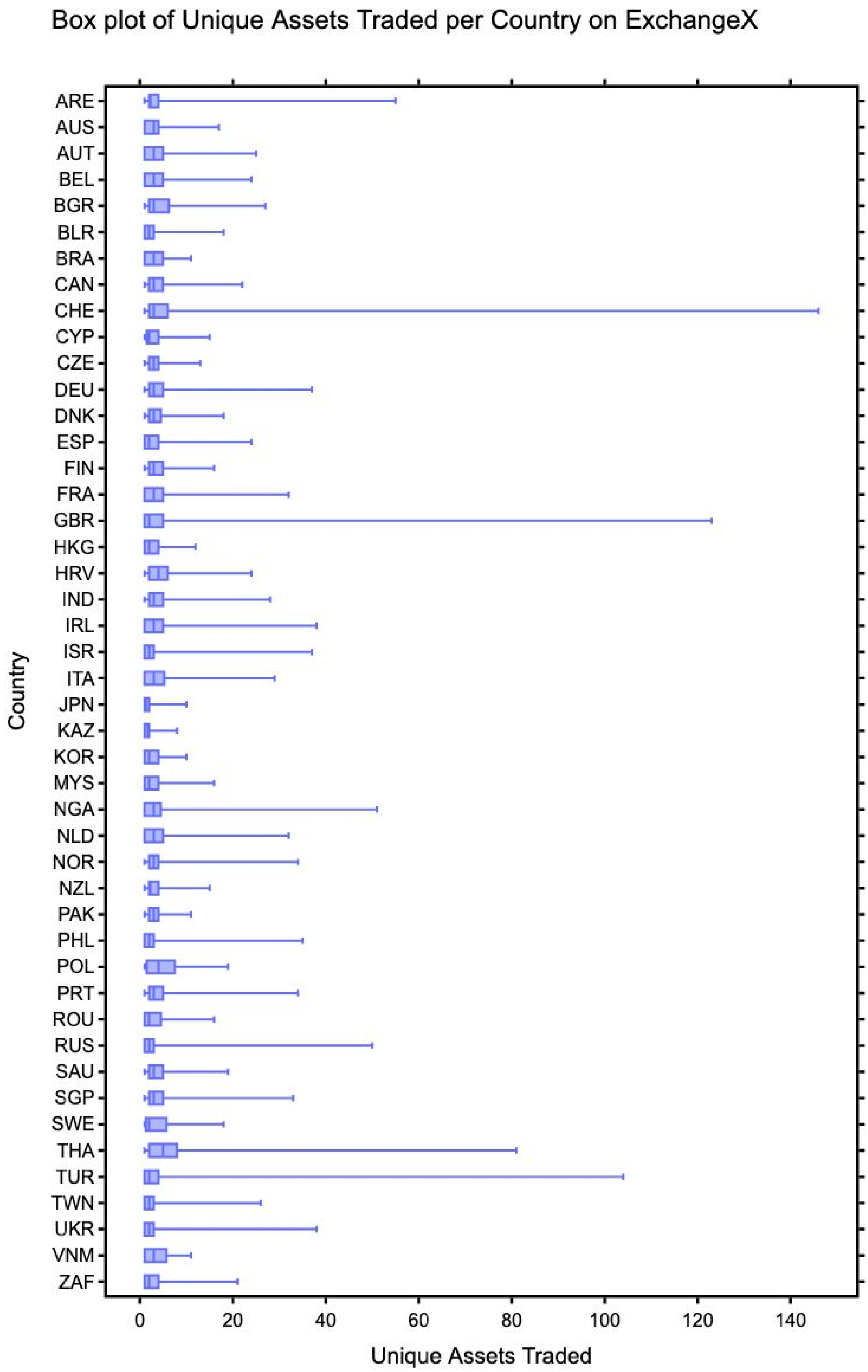
This figure shows box plot box plot of total number of trades per country for traders on ExchangeX

Figure 2.8: Distribution of Unique Number of Assets Traded on ExchangeX



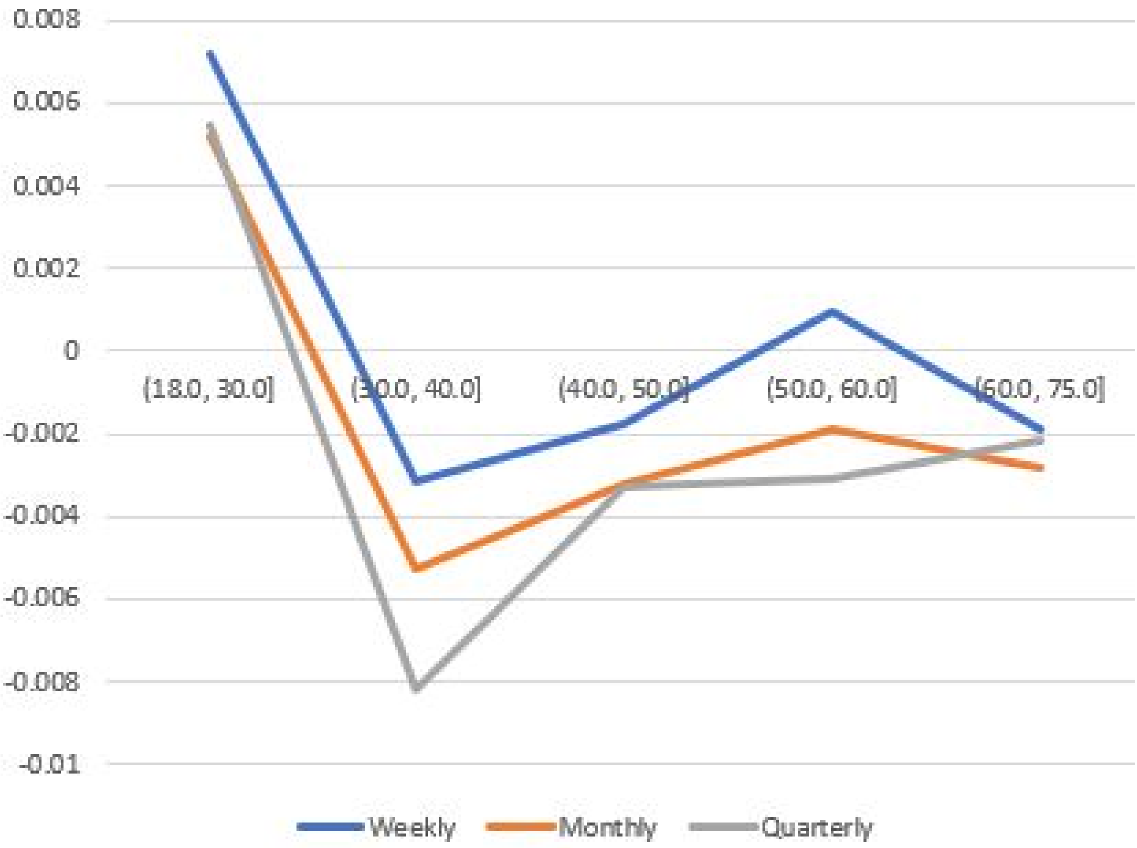
This figure shows distribution of unique number of assets traded on ExchangeX

Figure 2.9: Box Plot of Unique Number of Assets Traded per Country for Traders on ExchangeX



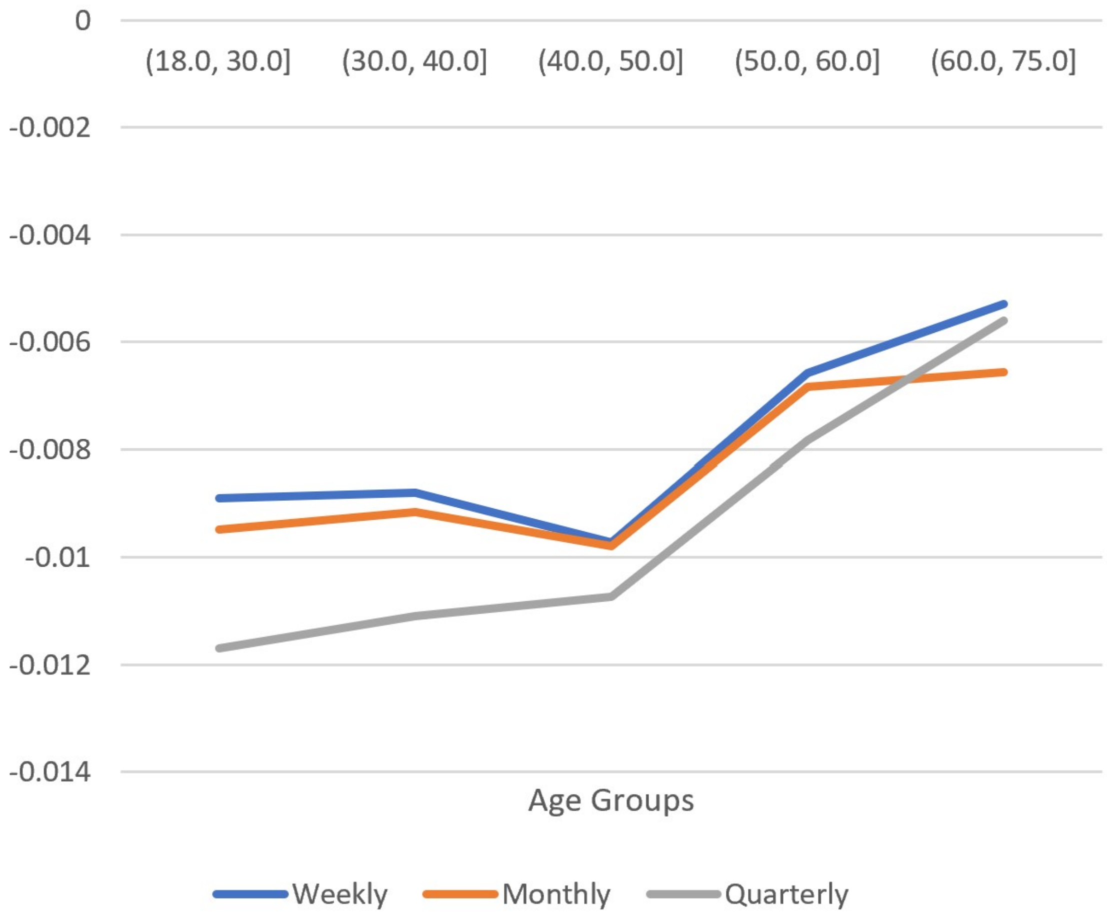
This figure shows box plot of unique number of assets traded per country for traders on ExchangeX

Figure 2.10: Disposition Spreads on a Transaction Level Calculated on a Weekly, Monthly and Quarterly Basis Based on US Dollars



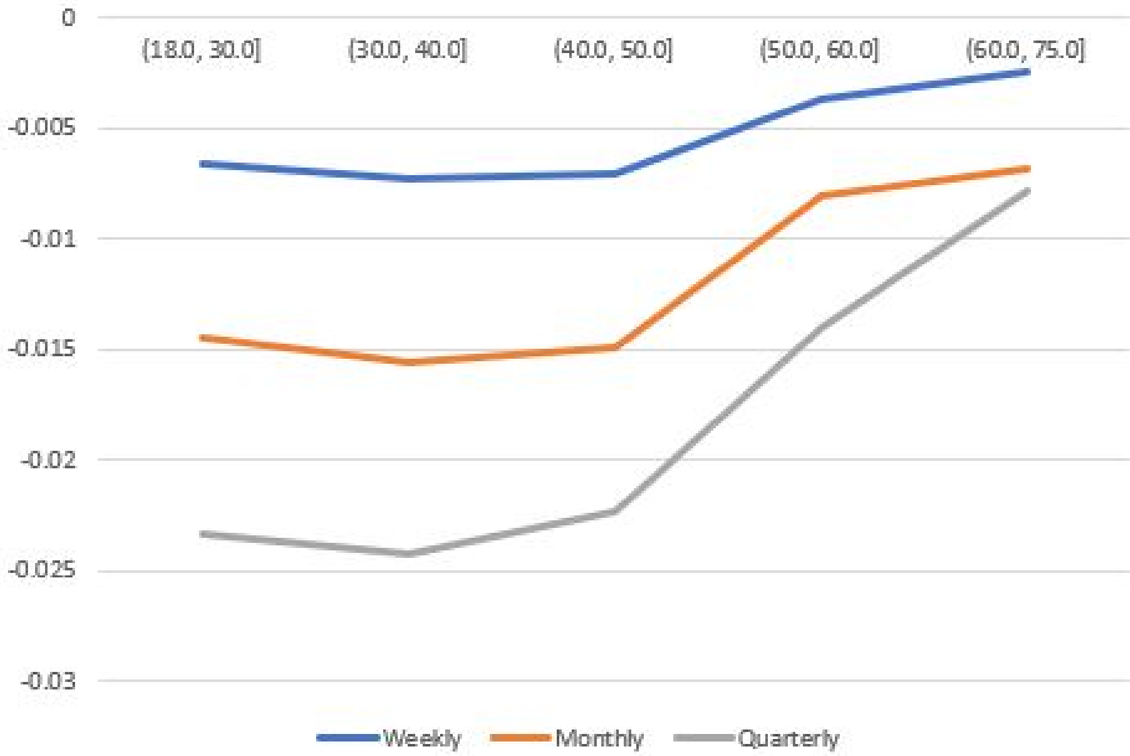
This figure shows graph of disposition spreads on a transaction level calculated on a weekly, monthly and quarterly basis based on US dollars, indicating the presence of a positive disposition effect for the youngest age group only. Disposition spreads for all 3 frequencies (weekly, monthly and quarterly) drop from a positive value to around zero, as age increase

Figure 2.11: Disposition Spreads on a Transaction Level Calculated on a Weekly, Monthly and Quarterly Basis Based on Counts



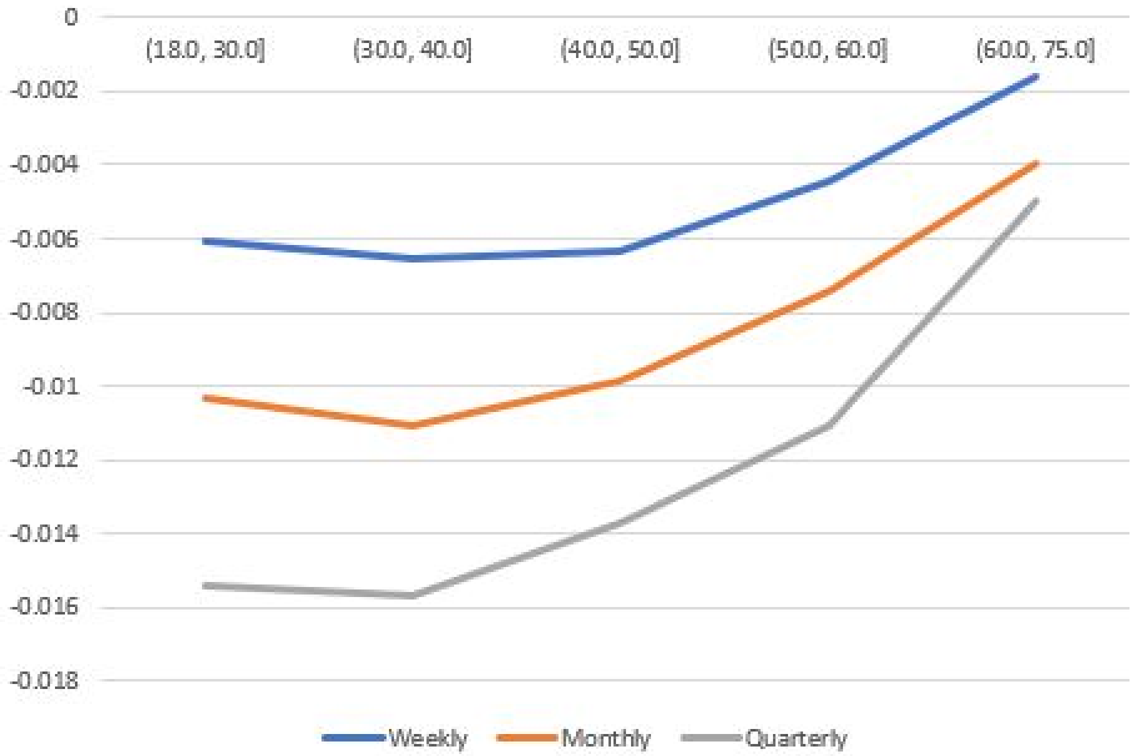
This figure shows graph of disposition spreads on a transaction level calculated on a weekly, monthly and quarterly basis based on counts. We can see that the age groups from 18 to 50 exhibit a strong anti-disposition effect, while groups of traders who are from 60 to 75 years old have a less pronounced anti-disposition effect

Figure 2.12: Disposition Spreads on a Individual Level Calculated on a Weekly, Monthly and Quarterly Basis Based on US Dollars



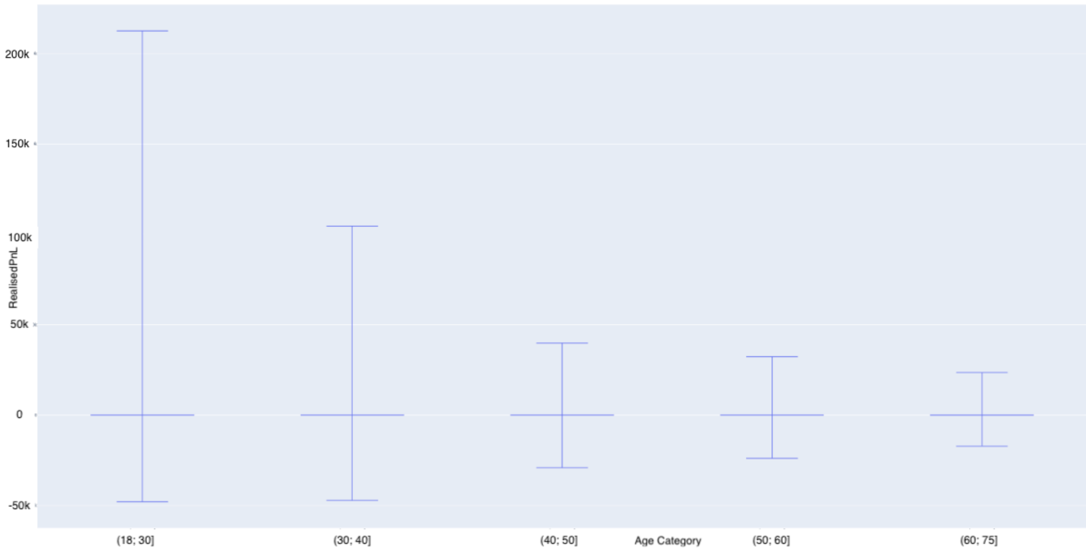
This figure shows graph of disposition spreads on an individual level calculated on a weekly, monthly and quarterly basis based on US Dollars. The results on counts are generally similar to those on US Dollars, where the anti-disposition effect declines with age, but here the longer the frequency (quarterly vs monthly vs weekly), the more pronounced the anti-disposition effect is.

Figure 2.13: Disposition Spreads on an Individual Level Calculated on a Weekly, Monthly and Quarterly Basis Based on Counts



This figure shows graph of disposition spreads on an individual level calculated on a weekly, monthly and quarterly basis based on counts. The results on counts are generally similar to those on US Dollars, where the anti-disposition effect declines with age, but here the longer the frequency (quarterly vs monthly vs weekly), the more pronounced the anti-disposition effect is.

Figure 2.14: Box plots of the realised profits of all trades, categorised by age categories



This figure shows box plots of the realised profits of all trades, categorised by age groups. Traders in the youngest age group of 18-30 have larger positive realised profits, then traders in other age groups, which pushes the measured disposition effect for them in the classical direction.

Figure 2.15: [Disposition Spread (Trade Count) Distribution of Traders on ExchangeX

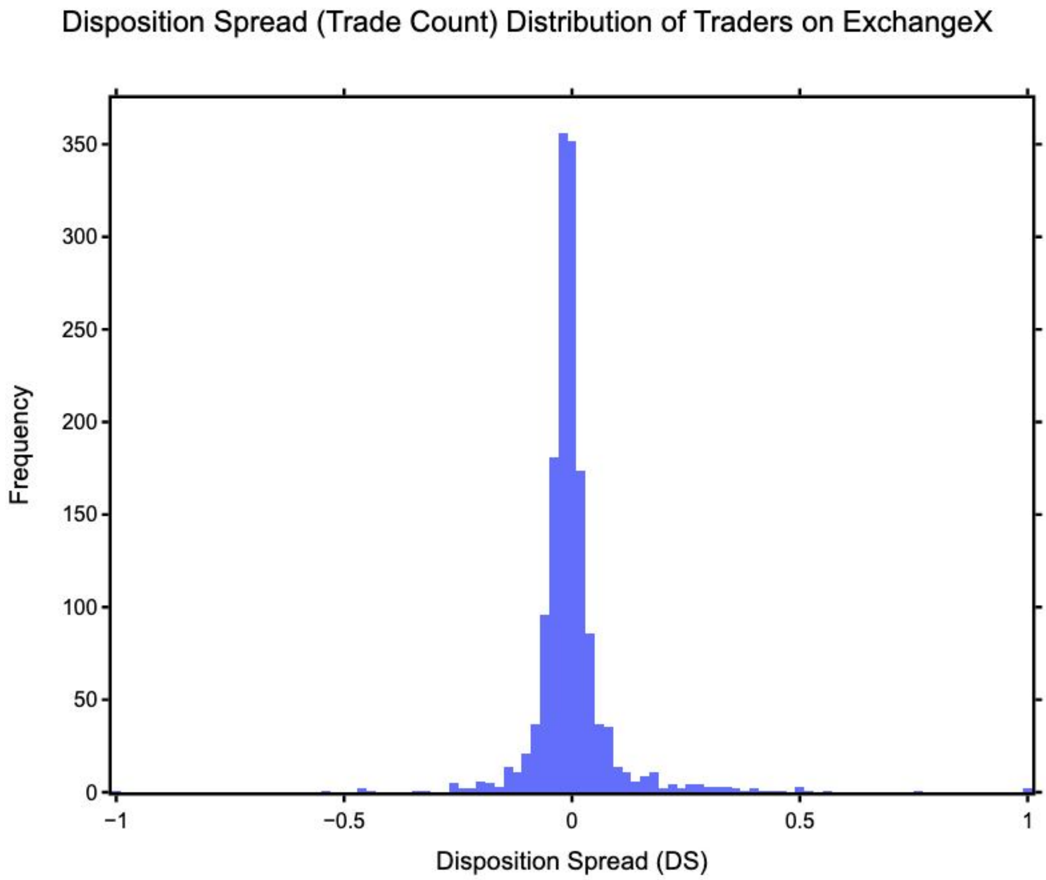


Figure 2.16: [Disposition Spread (Dollar Amount) Distribution of Traders on ExchangeX

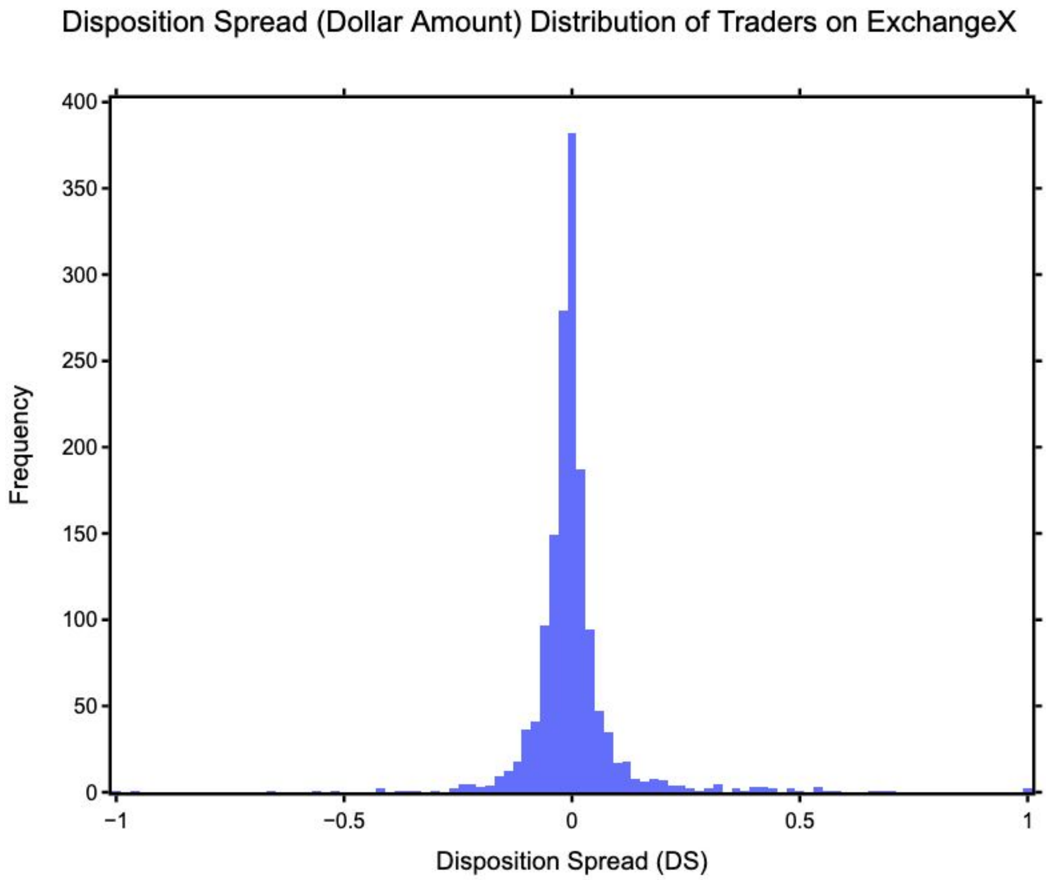


Figure 2.17: [Box Plot of Disposition Spread (Trade Count) per Country for Traders on ExchangeX

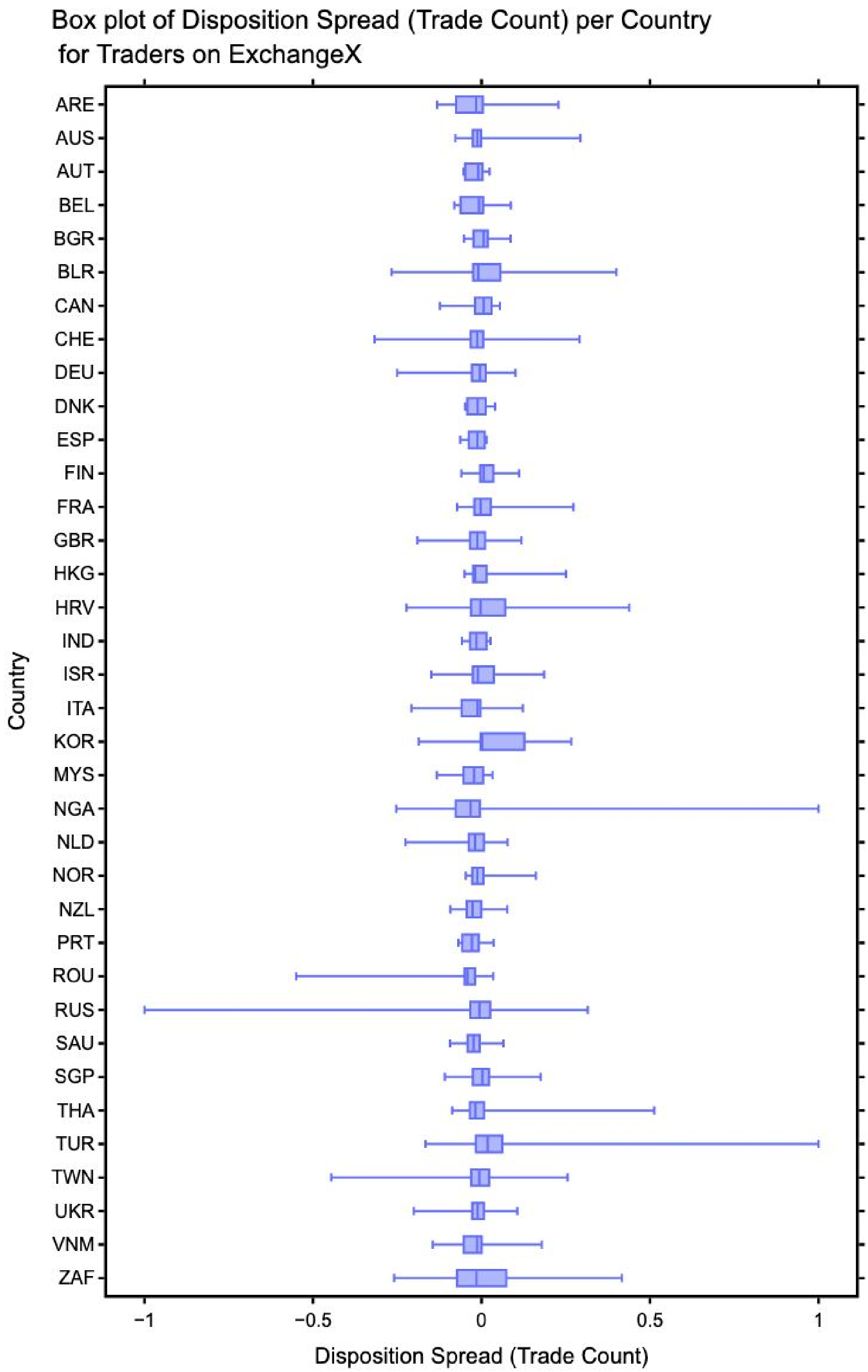


Figure 2.18: [Box Plot of Disposition Spread (Trade Count) per Country for Traders on ExchangeX

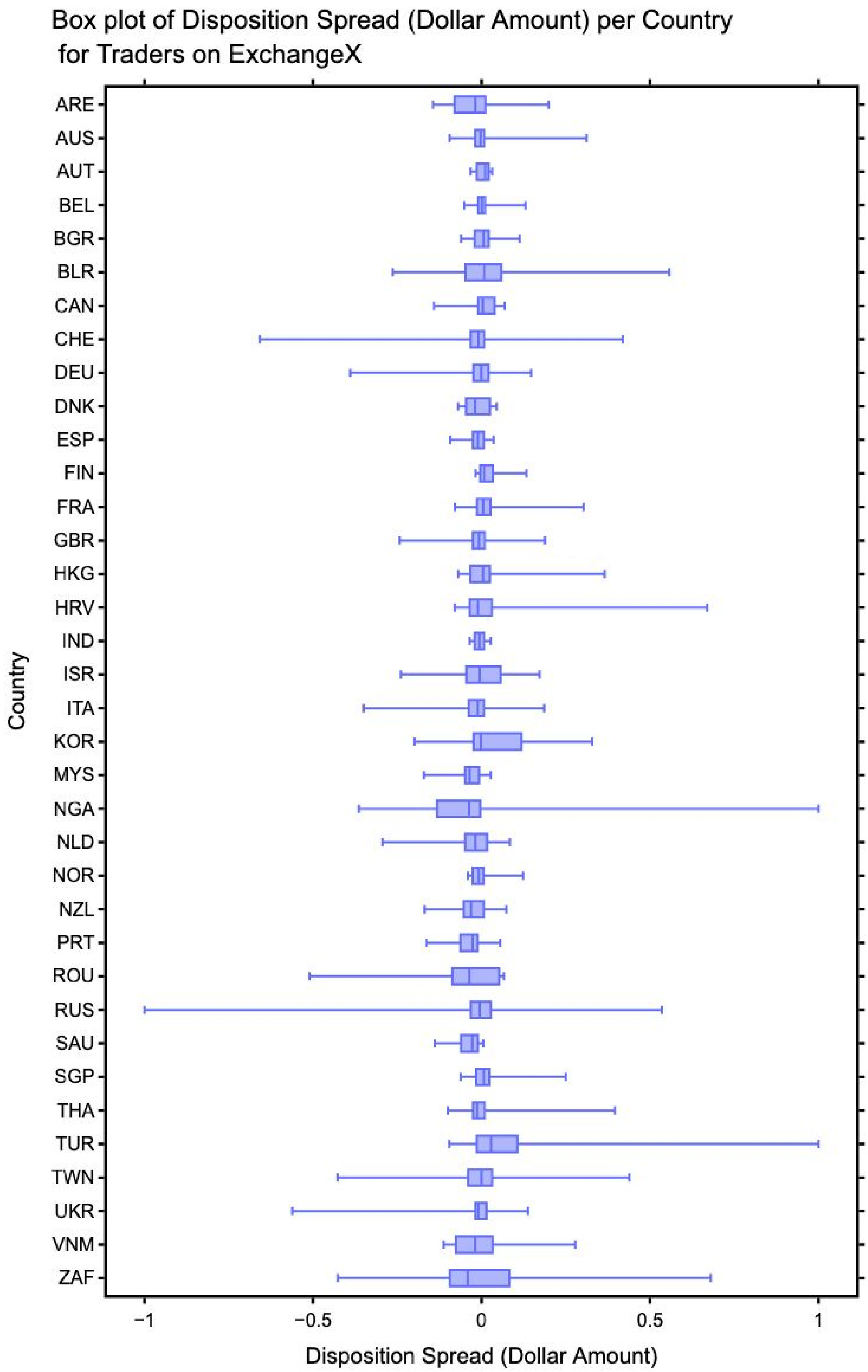


Table 2.1: Descriptive Statistics and Performance Measures of ExchangeX from June 2017 to December 2018. The following table shows descriptive statistics of traders on ExchangeX, as well as information on return on investment (Return) for traders on the platform. *Age of the Account* is the life of the account, *Age* is the age of the trader.
Number of Assets Traded is the number of assets the trader has used, *Number of Trades* is the number of trades filled and *Size of the Trade, USD* is the average size of a trade. *Return* shows the performance of market participants. $Return_{Unrealised}$ is the return component, which reflects the holding of inventory. $Return_{Realised}$ is the component that captures active portfolio management skills of a trader. $Return_{Total}$ is the sum of two components above. All *Return* metrics are in USD and on a daily basis.

Panel A: Trader Descriptive Statistics						
	Min.	**1st Q.**	**Mean**	**Median**	**3rd Q.**	**Max.**
Age of the Account, days	1	4	101	27	188	545
Age, years	20	29	37	34	41	71
Number of Assets Traded	2	2	3	3	3	65
Number of Trades	1	8	91	19	29	50,871
Size of the Trade, USD	1	14	489	201	409	620,021
Panel B: Return Metrics						
Return˙Unrealised, USD	-16.22%	-0.82%	0.23%	0.16%	0.56%	16.44%
Return˙Realised, USD	-8.54%	-1.69%	-0.76%	-0.45%	0.18%	5.98%
Return˙Total, USD	-16.22%	-0.67%	0.11%	0.16%	0.49%	15.26%

Table 2.2: Results of calculations of PGR, PLR and their differences and ratios for traders on crypto ExchangeX from June 2017 to December 2018. The following table shows results of calculations of PGR, PLR and their differences and ratios for traders on ExchangeX.

Panel A: Results based on US dollars			
	Weekly	**Monthly**	**Quarterly**
PL	7,234,266	31,602,321	85,777,730
PG	8,299,247	36,254,608	98,405,365
RL	106,141	463,671	1,258,536
RG	110,165	481,249	1,306,249
PGR	0.01819	0.01187	0.01311
PLR	0.01789	0.01388	0.01558
DS	0.00029	-0.00201	-0.00246
DR	1.77667	0.85974	0.85481
Tstat	-4.42268	73.59396	141.02036
Panel B: Results based on counts			
PL	33,318	145,550	395,066
PG	36,381	158,928	431,376
RL	833	3,639	9,877
RG	681	2,973	8,070
PGR	0.02447	0.02278	0.02477
PLR	0.03183	0.03018	0.03341
DS	-0.00736	-0.0074	-0.00864
DR	0.97132	0.82266	0.79879
Tstat	5.92261	12.81599	23.54642

Table 2.3: Results of individual level calculations of PGR, PLR and their differences and ratios for traders on crypto ExchangeX from June 2017 to December 2018. The following table shows results of calculations of PGR, PLR and their differences and ratios for traders on ExchangeX.

Panel A: Results based on US dollars			
	Weekly	**Monthly**	**Quarterly**
PL	786.3508	3,043.278	7,205.263
PG	850.7418	3,363.019	7,995.873
RL	12.62908	48.66201	115.9209
RG	12.28292	47.58111	113.2642
PGR	0.01776	0.025723	0.036047
PLR	0.02337	0.0376	0.054365
DS	-0.00527	-0.01116	-0.01777
DR	0.462314	0.622785	0.65242
Tstat	0.80324	2.721077	5.447672
Panel B: Results based on counts			
PL	3.212346	12.98526	31.68939
PG	3.418808	13.93036	34.18895
RL	0.100137	0.388149	0.909879
RG	0.076852	0.29975	0.710255
PGR	0.019141	0.023433	0.02809
PLR	0.024064	0.030754	0.039971
DS	-0.00475	-0.00788	-0.01147
DR	0.486317	0.601898	0.649452
Tstat	0.044099	0.135513	0.268423

Table 2.4: Disposition effect calculations at the transaction level for traders on crypto ExchangeX over the two periods, pre-peak (June 2017 to January 2018) and post peak (January 2018 to December 2018). The following table shows results of calculations of PGR, PLR and their differences and ratios for traders on ExchangeX over the two sub-sample periods designating a pre-peak or bullish period (from June 2017 to January 2018) and a bearish period (from January 2018 to December 2018).

	Bull Market			Bear Market		
	Weekly	Monthly	Quarterly	Weekly	Monthly	Quarterly
Panel A: Results based on US dollars						
PL	8523784.61	34095138.43	68190276.86	6368523.65	27596935.82	82790807.47
PG	8689911.64	34759646.56	69519293.12	7930985.93	34367605.68	103102817.03
RL	121295.80	485183.20	970366.39	95060.39	411928.37	1235785.11
RG	112613.64	450454.54	900909.09	106813.61	462859.00	1388576.99
PGR	0.03	0.02	0.02	0.01	0.01	0.01
PLR	0.03	0.02	0.02	0.01	0.01	0.01
DS	0.01	0.00	0.00	0.00	0.00	0.00
DR	2.50	1.05	1.15	1.34	0.83	0.85
tstat	-73.43	31.41	81.72	53.81	88.18	101.25
Panel A: Results based on Trade Count						
PL	17493.28	69973.13	139946.25	42535.85	184322.00	552966.00
PG	17273.09	69092.38	138184.75	47512.48	205887.42	617662.25
RL	962.38	3849.50	7699.00	741.02	3211.08	9633.25
RG	722.13	2888.50	5777.00	645.13	2795.58	8386.75
PGR	0.04	0.04	0.04	0.02	0.01	0.01
PLR	0.05	0.05	0.05	0.02	0.02	0.02
DS	-0.01	-0.01	-0.01	0.00	0.00	0.00
DR	0.90	0.82	0.89	1.02	0.87	0.85
tstat	5.28	10.02	10.73	5.09	9.10	17.80

Table 2.5: Results of calculations on transaction level of PGR, PLR and their differences and ratios based on minimum number of trades executed for traders on crypto ExchangeX from June 2017 to December 2018. The following table shows results of calculations of PGR, PLR and their differences and ratios for traders on ExchangeX for different minimum number of trades executed.

Mininum # Trades	10			30			50		
	Weekly	Monthly	Quarterly	Weekly	Monthly	Quarterly	Weekly	Monthly	Quarterly
Panel A: Results based on US Dollars									
PL	5924170.151	25879269.608	70243731.793	4980556.086	21757166.062	59055165.025	4093577.878	17882471.783	48538137.698
PG	6794798.912	29682542.617	80566901.389	5790354.316	25294705.695	68657058.316	4782726.022	20892961.045	56709465.693
RL	96084.163	419736.082	1139283.652	75963.324	331839.784	900707.985	60212.686	263034.363	713950.414
RG	105084.247	459052.238	1245998.932	89964.245	393001.702	1066718.906	78957.680	344920.392	936212.492
PGR	0.021	0.014	0.015	0.022	0.014	0.015	0.024	0.014	0.016
PLR	0.021	0.016	0.018	0.022	0.016	0.017	0.021	0.016	0.017
DS	0.001	-0.002	-0.002	0.001	-0.002	-0.002	0.003	-0.001	-0.001
DR	1.817	0.891	0.885	2.008	0.910	0.901	2.243	0.994	0.988
tstat	-7.728	58.670	111.423	-5.651	61.921	110.711	-27.776	32.022	57.621
Panel B: Results based on counts									
PL	11451.060	50023.053	135776.857	5465.024	23873.526	64799.571	3421.301	14945.684	40566.857
PG	12276.518	53629.000	145564.429	5835.446	25491.684	69191.714	3652.687	15956.474	43310.429
RL	719.325	3142.316	8529.143	532.867	2327.789	6318.286	421.494	1841.263	4997.714
RG	615.048	2686.789	7292.714	495.663	2165.263	5877.143	417.590	1824.211	4951.429
PGR	0.057	0.053	0.056	0.088	0.083	0.085	0.112	0.107	0.108
PLR	0.068	0.065	0.070	0.097	0.093	0.099	0.119	0.114	0.119
DS	-0.011	-0.011	-0.014	-0.009	-0.010	-0.013	-0.006	-0.007	-0.011
DR	1.003	0.863	0.839	1.053	0.915	0.890	1.090	0.954	0.927
tstat	3.588	8.027	15.650	1.816	4.169	8.781	0.889	2.173	5.296

Table 2.6: Results of calculations on individual level of PGR, PLR and their differences and ratios based on minimum number of trades executed for traders on crypto ExchangeX from June 2017 to December 2018. The following table shows results of calculations of PGR, PLR and their differences and ratios for traders on ExchangeX for different minimum number of trades executed.

Minimum # trades	10			30			50		
	Weekly	Monthly	Quarterly	Weekly	Monthly	Quarterly	Weekly	Monthly	Quarterly
Panel A: Results based on US Dollars									
PL	1752.785	6826.274	16407.311	3033.981	11990.453	29452.302	3995.218	15901.960	39235.129
PG	1927.937	7641.687	18418.772	3409.023	13660.648	33604.335	4521.128	18210.061	44994.178
RL	30.089	116.927	282.876	48.828	192.511	474.284	61.857	246.103	610.087
RG	31.040	121.082	293.707	53.837	213.148	527.257	74.846	298.973	746.430
PGR	0.039	0.054	0.071	0.058	0.075	0.092	0.071	0.088	0.105
PLR	0.049	0.073	0.098	0.065	0.090	0.115	0.075	0.100	0.124
DS	-0.009	-0.018	-0.026	-0.007	-0.015	-0.022	-0.004	-0.012	-0.019
DR	0.554	0.697	0.778	0.588	0.811	0.887	0.732	0.885	0.947
tstat	1.383	4.632	8.907	1.269	4.576	9.408	0.845	3.727	8.702
Panel B: Results based on counts									
PL	3.2306	13.0451	31.9777	3.2369	13.1533	32.7050	3.2393	13.2328	33.0224
PG	3.3900	13.8103	34.0207	3.3907	13.8876	34.6552	3.3907	13.9523	34.9393
RL	0.2275	0.8892	2.1176	0.3422	1.3592	3.3076	0.4288	1.7204	4.2148
RG	0.1850	0.7288	1.7549	0.3034	1.2143	2.9847	0.4039	1.6320	4.0363
PGR	0.0439	0.0496	0.0589	0.0672	0.0745	0.0843	0.0855	0.0937	0.1033
PLR	0.0527	0.0638	0.0780	0.0757	0.0877	0.1021	0.0922	0.1041	0.1184
DS	-0.0087	-0.0138	-0.0189	-0.0085	-0.0130	-0.0176	-0.0066	-0.0105	-0.0151
DR	0.5344	0.6831	0.7575	0.6244	0.7957	0.8637	0.6927	0.8707	0.9290
tstat	0.0544	0.1630	0.3170	0.0444	0.1315	0.2637	0.0317	0.0964	0.2091

Table 2.7: Results of calculations on individual level of PGR, PLR and their differences and ratios based on quintiles of average trade size for traders on ExchangeX from June 2017 to December 2018. The following table shows results of calculations of PGR, PLR and their differences and ratios for traders on ExchangeX for different quintiles of the average trade size of trades on ExchangeX.

	Q_1			Q_2			Q_3			Q_4			Q_5		
	Weekly	Monthly	Quarterly	Weekly	Monthly	Quarterly	Weekly	Monthly	Quarterly	Weekly	Monthly	Quarterly	Weekly	Monthly	Quarterly
Panel A: Results based on US Dollars															
PL	2704191.637	11813047.679	32063986.556	2837756.893	12396516.952	33647688.869	2896760.180	12654268.154	34347299.276	3738107.066	16329625.604	44323269.495	5159174.200	22537445.200	61173065.500
PG	3291142.671	14377096.932	39023548.816	3394004.598	14826441.141	40243197.382	3458176.118	15106769.356	41004088.253	4359637.699	19044733.104	51692846.997	5855379.230	25578761.900	69428068.100
RL	11816.327	51618.693	140107.880	20360.227	88942.042	241414.114	33409.328	145946.013	396139.177	53865.490	235307.140	638690.808	79926.807	349153.947	947703.571
RG	19543.325	85373.472	231727.995	30165.396	131775.151	357675.411	42394.202	185195.726	502674.114	59326.516	259163.201	703442.975	73206.278	319795.844	868017.292
PGR	0.020	0.015	0.017	0.023	0.020	0.025	0.022	0.015	0.018	0.019	0.011	0.012	0.018	0.011	0.012
PLR	0.013	0.010	0.011	0.015	0.011	0.013	0.019	0.015	0.017	0.018	0.014	0.014	0.020	0.015	0.017
DS	0.007	0.005	0.006	0.008	0.008	0.012	0.003	0.000	0.001	0.001	-0.003	-0.002	-0.002	-0.004	-0.004
DR	4.860	1.393	1.352	2.301	1.275	1.433	1.919	0.998	0.982	1.963	0.834	0.846	1.707	0.776	0.760
tstat	-66.878	-116.442	-213.267	-71.750	-176.870	-387.867	-25.858	-3.593	-21.545	-14.348	66.407	89.281	22.562	113.736	210.991
Panel B: Results based on counts															
PL	6757.048	29517.632	80119.286	7624.470	33306.895	90404.429	7863.072	34349.211	93233.571	7753.614	33871.053	91935.714	6470.265	28264.842	76718.857
PG	7336.181	32047.526	86986.143	8216.819	35894.526	97428.000	8456.277	36940.579	100267.286	8314.193	36319.895	98582.571	6916.687	30215.000	82012.143
RL	276.446	1207.632	3277.857	343.518	1500.632	4073.143	379.169	1656.368	4495.857	372.024	1625.158	4411.143	291.048	1271.421	3451.000
RG	225.675	985.842	2675.857	292.084	1275.947	3463.286	327.687	1431.474	3885.429	324.542	1417.737	3848.143	251.386	1098.158	2980.714
PGR	0.037	0.035	0.036	0.043	0.040	0.042	0.046	0.043	0.045	0.045	0.043	0.045	0.042	0.039	0.042
PLR	0.048	0.046	0.049	0.051	0.049	0.053	0.054	0.051	0.056	0.053	0.051	0.056	0.049	0.047	0.052
DS	-0.011	-0.011	-0.013	-0.009	-0.009	-0.011	-0.008	-0.009	-0.011	-0.008	-0.008	-0.011	-0.007	-0.008	-0.010
DR	0.951	0.816	0.785	1.047	0.878	0.845	1.026	0.879	0.850	1.011	0.869	0.845	0.986	0.854	0.835
tstat	3.303	6.858	13.037	2.693	5.948	11.652	2.520	5.632	11.191	2.376	5.414	10.679	2.062	4.884	9.601

Table 2.8: Results of calculations on transaction level of PGR, PLR and their differences and ratios for traders on crypto ExchangeX from June 2017 to December 2018. The following table shows results of calculations of PGR, PLR and their differences and ratios for traders on ExchangeX.

Panel A: Results based on US dollars				
Age Group		**Weekly**	**Monthly**	**Quarterly**
(18.0, 30.0]	DS	0.007199	0.005188	0.005454
	DR	2.094512	0.995008	1.012193
	T Statistics	-18.9618	-30.7741	-50.6449
(30.0, 40.0]	DS	-0.003126	-0.005248	-0.008214
	DR	1.592071	0.810904	0.786494
	T Statistics	18.5990	74.5841	176.134064
(40.0, 50.0]	DS	-0.001795	-0.003202	-0.003271
	DR	1.563247	0.647233	0.643399
	T Statistics	21.5310	97.2130	159.5567
(50.0, 60.0]	DS	0.000944	-0.001911	-0.003089
	DR	2.107849	0.820043	0.76002
	T Statistics	-6.2059	30.7553	76.6349
(60.0, 75.0]	DS	-0.001882	-0.002827	-0.002166
	DR	4.464667	0.778400	0.69046
	T Statistics	11.3675	45.0282	58.17392
Panel B: Results based on counts				
(18.0, 30.0]	DS	-0.008890	-0.009483	-0.011698
	DR	0.923311	0.778573	0.752698
	T Statistics	3.3187	7.6186	14.5751
(30.0, 40.0]	DS	-0.008789	-0.009156	-0.011090
	DR	0.993074	0.839106	0.815430
	T Statistics	3.4928	7.8126	14.8001
(40.0, 50.0]	DS	-0.009711	-0.009784256	-0.010733924
	DR	0.905988	0.780883	0.765829
	T Statistics	2.5569	5.5232	9.7345
(50.0, 60.0]	DS	-0.006568	-0.006840	-0.007831
	DR	0.971671	0.832402	0.809203
	T Statistics	1.1727	2.6241	4.7752
(60.0, 75.0]	DS	-0.005295	-0.006551	-0.005592
	DR	0.937134	0.694718	0.724662
	T Statistics	0.8133	2.2158	3.039745

Table 2.9: Results of calculations on individual level of PGR, PLR and their differences and ratios for traders on crypto ExchangeX from June 2017 to December 2018. The following table shows results of calculations of PGR, PLR and their differences and ratios for traders on ExchangeX.

Panel A: Results based on US dollars				
Age Group		**Weekly**	**Monthly**	**Quarterly**
(18.0, 30.0]	DS	-0.006659	-0.014478	-0.02338
	DR	406.9000	94.18472	69.62865
	T Statistics	0.4631	1.6056	3.2387
(30.0, 40.0]	DS	-0.007327	-0.015572	-0.024204
	DR	186.2069	166.9230	360.6180
	T Statistics	0.8263	2.8134	5.4932
(40.0, 50.0]	DS	-0.007003	-0.014882	-0.02231
	DR	157.7214	39.72844	64.29740
	T Statistics	1.6348	5.8092	11.2382
(50.0, 60.0]	DS	-0.003742	-0.008042	-0.014019
	DR	752.0064	2320.342	30.34336
	T Statistics	0.9035	3.3483	7.7093
(60.0, 75.0]	DS	-0.002478	-0.006844	-0.007868
	DR	8.920765	37.0291	16.26617
	T Statistics	1.0629	4.8077	7.6095
Panel B: Results based on counts				
(18.0, 30.0]	DS	-0.006043	-0.010365	-0.015394
	DR	0.398419	0.542150	0.616631
	T Statistics	0.0510	0.1620	0.3216
(30.0, 40.0]	DS	-0.006522	-0.011068	-0.015669
	DR	0.481651	0.617558	0.658495
	T Statistics	0.0510	0.1619	0.3123
(40.0, 50.0]	DS	-0.006340	-0.009837	-0.013693
	DR	0.511725	0.606750	0.654311
	T Statistics	0.05177	0.1552	0.3036
(50.0, 60.0]	DS	-0.004440	-0.007432	-0.01108
	DR	0.539465	0.633392	0.658410
	T Statistics	0.0372	0.1242	0.2684
(60.0, 75.0]	DS	-0.001609	-0.003959	-0.004992
	DR	0.434349	0.570761	0.614183
	T Statistics	0.02004	0.0886	0.1719

Chapter 3

Gambler's Fallacy in Cryptocurrency Markets

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Gambler's Fallacy in Cryptocurrency Markets

3.1 Introduction

Two important behavioural biases in financial markets are the gambler's fallacy and the hot hand fallacy, which alter the way people misinterpret random sequences. Specifically, individuals who are prone to the hot hand fallacy believe in positive autocorrelation of a non-autocorrelated sequence of events, such that they expect a historical trend to continue into the future. One manifestation of this phenomenon is when investors increasingly allocate funds to fund managers who have exhibited a successful performance record, in hopes that such success will be replicated in the future (Sirri & Tufano 1998, Barber et al. 2005). On the other hand, the gambler's fallacy occurs when individuals believe that a negative autocorrelation or mean-reversion exists within a non-correlated random sequence. A highly researched phenomenon, called the disposition effect, can be seen as an example of the gambler's fallacy, as investors sell winning investments prematurely, and hold on to losing ones (Odean 1998, Weber & Camerer 1998, Chen et al. 2007).

Many studies have shown that biased decisions can produce sub-par performance results for the decision maker. For example, investors who are prone to the hot hand fallacy within the mutual fund space tend to allocate more money to funds that have shown a history of outperformance (Brown et al. 1996, Chevalier & Ellison 1997, Sirri & Tufano 1998). Nevertheless, studies including Carhart (1997), Malkiel (2003), and Malkiel (2005) have shown that there is a lack of persistence in good performance across funds. Another study by Goetzmann & Kumar (2008) shows that investors who are prone to trade based on trends — whether they expect that trend to continue into the future (hot hand fallacy) or reverse (gambler's fallacy) — tend to hold less diversified portfolios, consequently leading to poor risk-adjusted performance.

While in traditional markets, e.g. equities, one can find abundant fundamental information about potential future investments, such degree of information and transparency is lacking in the cryptocurrency space. The reason is that most cryptocurrencies are decentralised with no identifiable entity that discloses audited information on a regular basis. Moreover, most trading happens on centralised cryptocurrency exchanges, implying that fund flows and movements are not necessarily recorded on the blockchain. Therefore, a significant proportion of crypto activities are veiled from public scrutiny. Consequently this environment raises the question of whether traders in the cryptocurrency space are prone to exhibiting biased trend-chasing decisions in the form of their the hot hand fallacy or the gambler's fallacy.

To investigate this, I use a proprietary data set from an anonymous cryptocurrency exchange, which I call ExchangeX, that includes over 1.5 million transactions executed by over 15,000 traders from June 2017 to December 2018. Using a series of regression models with different variations for estimating trader performance, I examine the relation between cryptocurrency traders' past performance and their future trade size. The idea is that those who exhibit the gambler's fallacy are likely to increase their trade size after experiencing poor past performance as they double down on future investments to make up for poor past decision. On the other hand, if the relation between past performance and future trade size is positive, then this suggests evidence of the hot hand fallacy, as traders believe that such good performance will persist into the future.

The results presented in this paper provide evidence supporting the existence of the gambler's fallacy among cryptocurrency traders, whereby individuals are likely to increase their position size after exhibiting poor past performance. Moreover, I find that when the market is trending in one direction, traders subsequently trade in the opposite direction, which suggests that they expect that the market will reverse direction. This implies that traders believe in some form of mean reversion, which further supports evidence of the gambler's fallacy.

My findings are of interest to both academics and practitioners as they highlight the extent to which trader decisions regarding their trade size and direction are influenced by past performance. This allows traders to be more aware of the bias or tendency that may drive them to adopt more of a gambler's approach to cryptocurrency trading, rather than a long-term fundamentalist approach based on the inherent value (Liu 2022, Kyriazis et al. 2020, Biais et al. 2020) embedded within the asset's technological innovation.

The remainder of this paper is divided as follows. Section 3.2 covers the literature on the gambler's fallacy both in traditional markets as well as in the cryptocurrency space. Section 3.3 explains the methodology used in this paper. Section 3.4 outlines the data set used as well as some descriptive statistics. Section 3.5 presents the results and discusses the findings. Finally, Section 3.6 concludes this paper.

3.2 Literature Review

Tversky & Kahneman (1971) discuss and show the irrationality of decision making in their work "Belief in the Law of Small Numbers."

The gambler's fallacy has been described as an individual's belief that a sequence of random outcomes represents the right proportion; this means that if a portion of the sequence has diverted from the entire proportion, then this will be corrected by an opposing outcome (Tversky & Kahneman 2004). The hot hand fallacy - on the other hand - is an individual's belief in observing a sequence of outcomes in random events with that sequence being a good indication of what to expect as the next outcome (Gilovich et al. 1985).

Gemayel & Preda (2021) state that the perception and trading ability of traders often changes on the basis of their previous performances and market events. They apply two models to study the performance of traders and how that affects the size of future trades in the cryptocurrency market, due to its ambiguity. The first model is a linear one that makes use of the natural logarithm at a certain time of the position size as the dependent variable and the second model is a logistic one that uses a binary dependent variable that is equal to unity when the position size at a certain time is greater than the overall mean position size, and null otherwise. After necessary regressions have been applied, the two models showed that the historical trading success ratio and future trade size are negatively correlated. In other words, a trader whose past trading success ratio is low, is more prone to inflate the size of future trades. Similarly, the size of future trades is more likely to increase for traders with low past passive returns. This pattern is in support of the argument that cryptocurrency traders show characteristics similar to those described in the gambler's fallacy, since it is analogous to the martingale betting system. Despite the vague nature of the trading environment, cryptocurrency traders believe they will make up for their large portion of incorrect past predictions by increasing their exposure on following trades and believe that ensuing predictions will be right. Hence, poor past performances drive future trading activities based on behavioural biases and fallacies.

Findings indicate that as individuals trade more, their future trading positions get larger. Adding to these findings that a lot of trading is harmful to traders' performance, one infers that cryptocurrency traders do not show ambiguity-averse characteristics and that their risk profile switches the more prolonged the trader is involved in the market. Due to no well defined connection linking future and historical trade sizes, greater amounts of available capital for investing lead the authors to find that greater exposure in future trades and trade balances are directly correlated for cryptocurrency traders. Volatility and future trade size are also directly correlated, which means that traders take advantage of possible profitable opportunities when volatility is high. The authors further state that age and position size are concavely correlated, which means that larger relative exposures on following trades is attributed to traders in the centre of the age spectrum. This may be due to them being wealthier in comparison to younger traders, having a better comprehension of cryptocurrencies in comparison to older traders, and their diminished aversion to ambiguity.

Stöckl et al. (2015) state that in financial markets, the hot hand fallacy bias is observable when investors entrust decisions to professionals. For instance, investors in general buy funds with a past of success, since they believe in the fund manager's abilities to prolong this success. Chevalier & Ellison (1997) find a positive relation for fund inflows and the historical rank of a mutual fund, due to the investor's belief in the hot hands of the mutual fund manager. Such behaviour leads to biased decisions based on the absence of perseverance in fund performance (Malkiel 2005). Negative or unfavourable consequences from decision makers can be a result of biased decisions (Stöckl et al. 2015). For example, Goetzmann & Kumar (2008) state that American investors who show characteristics of either the hot hand fallacy or gambler's fallacy, have negative risk and performance consequences due to less diversified portfolios. Both fallacies can be related to an increased chance of overdrawn bank accounts and long-term unemployment, respectively, in a different context. Evidence of both biases was found by Suetens et al. (2016), where data on lotto gambling was used. The gambler's fallacy was shown by players betting less on numbers raffled in the last seven days and the hot hand fallacy was shown by players betting more on numbers that were regularly raffled. Clotfelter & Cook (1991) state that fewer individuals bet on a number after it is raffled and that the winning number is as favoured as the mean number months later, as this effect diminishes.

In an experiment ran by Huber et al. (2010), both biases were investigated in a unified framework. A series of independent coin tosses showing equal probabilities of 0.5 for each of the heads and tails outcomes were presented to participants who can then choose to a) speculate the next outcome, b) pass-on the decision to experts, or c) take a risk-free payment. The participants would receive an amount valued at the experimental currency, Taler. An amount of 100 Taler is awarded for a right speculative decision, while 50 Taler are deducted for a wrong speculative decision. If option (b) is selected, the same payoff is rewarded as option (a), but a fee is deducted, and a selection of option (c) offers a reward of 10 Taler. Therefore, the options are designed such that option (c) is the preferred one for a risk neutral participant. The authors observe both fallacies in the participants' decisions. The more successful the expert has been in the past, the more frequently option (b) is selected, which suggests that participants expect hot hands with the expert's decisions. Whereas, the gambler's fallacy is seen in option (a) where participants choose heads less frequently after successions of heads, and vice versa with choosing tails.

Groups, such as the Federal Open Market Committee and the Governing Council of the European Central Bank, make decisions on monetary policy and other decisions of huge economic importance (Huber et al. 2010). The investment plan of a fund and which stocks to choose in financial markets, are decided upon by fund managers. Stöckl et al. (2015) find that group decision-making has a positive impact on decision quality. Groups in general perform just as well or better than individuals, no matter the decisions being made in strategic or non-strategic situations. The authors also state that they know little with regards to group decisions potentially affecting present behavioural biases in financial markets, even if group decision procedures are broadly implemented.

Croson & Sundali (2005) state that the beliefs related to the the first observation of the gambler's fallacy was in the laboratory in controlled states. Given two illuminating light bulbs, subjects in these experiments had to guess which of the two lights would then turn on. The subjects were more likely to guess the other after seeing a sequence of one outcome (Estes 1964).

The gambler's fallacy is also shown in horse racing (Metzger 1985), in that fewer bets are taken by individuals on the horse that has won the prior couple of races. Hence, in general, if the animal in post position 3 won the prior race, then the different animal in post position 3 is significantly under-bet in the current race (Terrell & Farmer 1996). Rabin (2002) finds that brief random sequences leads individuals to believe that these sequences should be representative of the underlying probability used to generate them. Hence, a black number has a better chance to occur after red numbers appearing thrice on the roulette wheel, since that sequence is more characteristic of the fundamental distribution than a sequence composed of four red numbers in a row. The authors also show that individuals pretend that independent and identically distributed arbitrary processes are selected from a finite basket without replacement and thus magnify the chances that brief sequences are good representations of long sequences, which leads to the beliefs of the gambler's fallacy. Gilovich et al. (1985) find that individuals trust in the hot hand fallacy when it comes to shooting basketballs, and that the basketball shooter's probability of success is uncorrelated.

Chau & Phillips (1995) show evidence from a lab experiment that simulates a blackjack game, that individuals increase their bets following a sequence of wins than they do after a sequence of losses, both when betting on their own and others' play. An investment game where a coin toss settled gains and losses, Shiv et al. (2005) have shown a tendency to quit after losses by healthy controls and brain-damaged control patients. On the contrary to that, the authors show that a surge in risky behaviour after a sequence of losses prevails in patients who have brain lesions that include the mesial orbifrontal cortex. Sharpe & Tarrier (1993) state that a possible clinical phenomenon of why a gambler may persist on gambling while experiencing accumulative losses, is known as pathological gambling. This allows the gambler to believe that their luck would change in the next round. Xue et al. (2011) suggest that impeded means of successful decision-making for the sorts of risky behaviours that underlie the gambler's fallacy arise in patients with brain lesions.

3.3 Methodology

I conduct multiple regression analyses in order to investigate the gambler's fallacy among cryptocurrency traders.

3.3.1 Trade Size

In the first set of models, I aim to examine whether a trader's past performance has any effect on future trade size. The idea is that, if the trader exhibits the gambler's fallacy, this means that larger negative past performance should be associated with larger future trade sizes. This is because the trader would expect that their subsequent prediction or trade will be correct despite the unpredictable nature of the cryptocurrency market, such that a larger position will make up for their previously wrong predictions as captured by their poor past performance. To run this analysis, I use the natural logarithm of the dollar value of transactions executed by trader j during period t as the dependent variable, denoted by $log(Volume)$. Regarding the control variables, I use several metrics to capture trader performance; however, I include these in separate models due to the high degree of multicollinearity. Specifically, Model (1.a) uses the total return (i.e. realised and unrealised) to capture overall performance, given by $TotalROI$, Model (1.b) uses the realised return to isolate performance due to active trading, given by $RealisedROI$, and Model (1.c) and Model (1.d) use dichotomised parameters of the total and realised returns, given by $TotalSR$ and $RealisedSR$, respectively. The latter two parameters aim to capture the success rate of the trader, irrespective of the magnitude of returns. Each of the previously mentioned performance metrics are estimated for each trader for the periods $t - q$, where $q = [1, 2]$ in order to capture the effects of historical performance on the size of future trades. Moreover, I include lagged values of $log(Volume)$ to capture any autocorrelation inherent in the size of transactions that is not driven by a reaction to performance. Additionally, I include control variables for each trader that are estimated up to but not including time t, such as the natural logarithm of the average trade size, $log(AverageTrade)$, the natural logarithm of the average balance size, $log(AverageBalance)$, the cumulative number of trades executed, $NumberTrades$, the number of unique markets traded, $NumberMarkets$, and the volatility of the cryptocurrency market, $Volatility$, proxied by the standard deviation of hourly price returns of the Bitcoin-Dollar market. I also control for demographics such as geographical location (as proxied by the *Continent* on which the trader is located, where *Continent* = [Africa, Americas, Asia, Europe, Oceania]) as well as age, given by the five age groups (18, 30], (30,40], (40,50], (50,60], and (60, 60+]. All models are augmented with trader fixed effects. Mathematically, I express the above-mentioned models as:

$$log(Volume)_{j,t} = \sum_{q=1}^{2} \beta_q TotalROI_{j,t-q} + Controls + \varepsilon_{n,t} \tag{1.a}$$

$$log(Volume)_{j,t} = \sum_{q=1}^{2} \beta_q RealisedROI_{j,t-q} + Controls + \varepsilon_{n,t} \tag{1.b}$$

$$log(Volume)_{j,t} = \sum_{q=1}^{2} \beta_q TotalSR_{j,t-q} + Controls + \varepsilon_{n,t} \tag{1.c}$$

$$log(Volume)_{j,t} = \sum_{q=1}^{2} \beta_q RealisedSR_{j,t-q} + Controls + \varepsilon_{n,t} \tag{1.d}$$

where

$$\begin{aligned} Controls = & \sum_{q=1}^{2} \gamma_q log(Volume)_{j,t-q} + \delta_1 log(AverageTrade)_{j,t} \\ & + \delta_2 log(AverageBalance)_{j,t} + \delta_3 NumberTrades_{j,t} \\ & + \delta_4 NumberMarkets_{j,t} + \sum_{q=0}^{2} \sigma_q Volatility_{t-q} \\ & + \sum_{l=(30,40]}^{L} \lambda_l Age_{j,l} + \sum_{c=Asia}^{C} \kappa_c Continent_{j,c} + \alpha_j + \upsilon_{j,t} \end{aligned}$$

The above-mentioned analyses aim to capture the effects of past performance on trade exposure in absolute terms. One caveat of this is that, if a trader is performing poorly over time, their future position sizes may naturally decrease since they are losing funds and would thus be unable to increase their position size in absolute terms. To address this, I run another set of logistic models — Models (2.a), (2.b), (2.c), and (2.d) — to investigate whether a trader's past performance drives the individual to increase or decrease their position size in relation to a rolling average of their trade size. Specifically, I compute a dichotomous dependent variable, labelled as $D(Volume)$, which takes the value of one if the trade size at time t is larger than the rolling average trade size over the period $t-1$ and $t-q$, where q

equals five[1]. I include the same set of control variables mentioned previously, and as such avoid repetition. The only difference however, is that I include the lag of $D(Volume)$ instead of $log(Volume)$ to capture any autocorrelation inherent in the size of transactions that is not driven by a reaction to performance. Mathematically, I write:

$$D(Volume)_{j,t} = \sum_{q=1}^{2} \beta_q TotalROI_{j,t-q} + Controls + \varepsilon_{n,t} \tag{2.a}$$

$$D(Volume)_{j,t} = \sum_{q=1}^{2} \beta_q RealisedROI_{j,t-q} + Controls + \varepsilon_{n,t} \tag{2.b}$$

$$D(Volume)_{j,t} = \sum_{q=1}^{2} \beta_q TotalSR_{j,t-q} + Controls + \varepsilon_{n,t} \tag{2.c}$$

$$D(Volume)_{j,t} = \sum_{q=1}^{2} \beta_q RealisedSR_{j,t-q} + Controls + \varepsilon_{n,t} \tag{2.d}$$

where

[1] As a robustness check, I use multiple values for q and obtain relatively similar conclusions for all values greater than five. Nonetheless, the reason I use five, is to ensure a sufficient number of transactions to calculate an average that is reflective of the trader's baseline trade size.

$$
\begin{aligned}
Controls = &\sum_{q=1}^{2} \gamma_q D(Volume)_{j,t-q} + \delta_1 log(AverageTrade)_{j,t} \\
&+ \delta_2 log(AverageBalance)_{j,t} + \delta_3 NumberTrades_{j,t} \\
&+ \delta_4 NumberMarkets_{j,t} + \sum_{q=0}^{2} \sigma_q Volatility_{t-q} \\
&+ \sum_{l=(30,40]}^{L} \lambda_l Age_{j,l} + \sum_{c=Asia}^{C} \kappa_c Continent_{j,c} + \alpha_j + \upsilon_{j,t}
\end{aligned}
$$

3.3.2 Net Crypto Exposure

The analyses presented in the previous section investigate the relation between trader past performance and the size of their future trades or bets. As an alternative approach to investigating the gambler's fallacy, I examine the relation between past performance and the net crypto exposure of traders on the exchange. To do so, I calculate the dollar value of the balance of each asset in a trader's account, and then calculate the proportion of crypto exposure relative to fiat over time. This metric allows us to test whether past performance impacts the composition, and thus the overall exposure, of traders to crypto assets. As such, I run another set of models where I compute the dependent variable, labelled as $\%(CryptoExposure)$, which represents the proportion of a trader's assets that are in crypto instead of fiat at any given time t.

I include the same set of control variables mentioned previously, and as such avoid repetition. The only difference however, is that I include the lag of $\%(CryptoExposure)$ instead of $log(Volume)$ to capture any autocorrelation inherent in portfolio composition. Mathematically, these models can be expressed as:

$$\%(CryptoExposure)_{j,t} = \sum_{q=1}^{2} \beta_q TotalROI_{j,t-q} + Controls + \varepsilon_{n,t} \tag{3.a}$$

$$\%(CryptoExposure)_{j,t} = \sum_{q=1}^{2} \beta_q RealisedROI_{j,t-q} + Controls + \varepsilon_{n,t} \tag{3.b}$$

$$\%(CryptoExposure)_{j,t} = \sum_{q=1}^{2} \beta_q TotalSR_{j,t-q} + Controls + \varepsilon_{n,t} \tag{3.c}$$

$$\%(CryptoExposure)_{j,t} = \sum_{q=1}^{2} \beta_q RealisedSR_{j,t-q} + Controls + \varepsilon_{n,t} \tag{3.d}$$

where

$$\begin{aligned} Controls = & \sum_{q=1}^{2} \gamma_q \%(CryptoExposure)_{j,t-q} + \delta_1 log(AverageTrade)_{j,t} \\ & + \delta_2 log(AverageBalance)_{j,t} + \delta_3 NumberTrades_{j,t} \\ & + \delta_4 NumberMarkets_{j,t} + \sum_{q=0}^{2} \sigma_q Volatility_{t-q} \\ & + \sum_{l=(30,40]}^{L} \lambda_l Age_{j,l} + \sum_{c=Asia}^{C} \kappa_c Continent_{j,c} + \alpha_j + \upsilon_{j,t} \end{aligned}$$

3.3.3 Trade Direction

Several studies (Pelster 2020, Rabin & Vayanos 2010) have investigated the gambler's fallacy in terms of trade direction. Specifically, Rabin & Vayanos (2010) argue that the gambler's fallacy can be identified by looking for reversals in the trade direction after short streaks, as opposed to long streaks of the same direction, which may be an indication of the hot hand fallacy. Pelster (2020) applied this methodology to test if traders bet on reversals or continuation of market trends, based on price alerts sent to traders. If traders sell (buy) when the market is trending upwards (downwards), this may be an indication of the gambler's fallacy. On the contrary, if traders buy (sell) when the market is trending upwards (downwards), this may suggest evidence of the hot hand fallacy.

In the spirit of Pelster (2020), I examine the direction in which traders trade in relation to how the market had been trending prior to the execution of the trade. Thus, the market trend parameters aim to capture whether traders perceive a trend reversal in the market, which would imply evidence of the gambler's fallacy. Specifically, a trader exhibits the gambler's fallacy if they show a negative relation between contemporary trade direction and lagged market trend parameters (i.e. they are trading in the opposite direction of the market as they expect a trend reversal).

One key difference between the cryptocurrency exchange data used in my study and the data used in the literature from traditional brokerages is that traders on most crypto exchanges can deposit funds in both fiat and crypto, and can trade into other crypto assets without necessarily trading into fiat. For example, a trader can deposit Bitcoin into their account, trade it for Ethereum (another cryptocurrency), then trade again into Ripple (yet another cryptocurrency) before trading back into Bitcoin or fiat. This raises the question: how do we categorise these different transactions into buy and sell positions in relation to a trader's intention and expectation of future market movements? In other words, is a buy trade from fiat to crypto considered similarly as a buy trade from crypto to crypto?

For the purpose of this analysis, I consider only transactions that shift funds from fiat to crypto, and vice versa, as actions that give an indication of a trader's expectation of the market. Consequently, transactions from crypto to crypto, or fiat to fiat, do not indicate a change in the trader's expectation within these respective markets. As such, I create a binary variable, called *Direction*, which takes the value of one if the trader exchanges fiat to crypto, and zero if the trader exchanges crypto to fiat. Under Model (3), I regress this variable on lagged market trends, given by $Trend_{t-q}$, where $q = [1, \ldots, 5]$. Mathematically, the general regression model is written as

$$Direction_{i,j,t} = \alpha_j + \beta_{i-k} Direction_{i-k,j,t} + \gamma_{t-q} Trend_{t-q} \tag{4}$$

where $Direction_{i,j,t}$ is the binary variable indicating the direction of trade i of trader j at time t, and $Trend_{t-q}$ is a binary variable that captures the market trend directions over periods $t-q$, and is equal to one if the general crypto market[2]

[2] I create a market weighted index of the top ten cryptocurrencies, and use the period-return

is trending upwards, and zero if downwards.

3.3.4 Accounting for Survivorship Bias

One important consideration when working with panel data is survivorship bias, which may arise from sample selection as subjects drop out of the overall sample over time. In this study, survivorship bias may lead us to underweight those who have performed poorly in the past and overweight those who have performed well, consequently leading us to finding greater evidence in support of the hot hand fallacy rather than the gambler's fallacy. This happens as traders who perform well will remain in the sample over time, and may naturally increase the size of their future trades. As such, this would result in us finding a positive relationship between future traded size and past performance. In order to mitigate this, I adopt the procedure proposed by Heckman (1976), which uses a two-step model to estimate efficient model parameters and standard errors. Specifically, I first apply a selection equation to capture the probability of a trader surviving to the next period, and then use this probability in the second-step model to control for survivorship bias. Hayley & Marsh (2016) adopt this correction methodology in their study and argue that using a daily sampling frequency is not recommended since that would imply that the model is capturing a trader's decision to trade in the market each day, which in itself may be affected by external factors, such as personal commitments. Thus, I use a weekly sampling frequency in my analyses.

The first-step probit selection model aims to forecast which individuals will be

---

of the index to identify the trend of the overall cryptocurrency market.

observable in the second-step model for each weekly cross-section. The conditional probability that a trader will survive is captured by the inverse Mills' ratio, denoted by λ, and is included in the second-step model. This is written as,

$$y_{j,t} = \alpha_j + x'_{j,t}\beta + \rho_1 I(t=1)\lambda_1 + \ldots + \rho_T I(t=T)\lambda_T + \epsilon_{j,t},$$

where $y_{j,t}$ and $x'_{j,t}$ are the dependent and independent variables, respectively, based on the analysis being conducted as discussed in Sections 3.3.1 and 3.3.3, $\lambda_1, \ldots, \lambda_T$ are the inverse Mills' ratios from the first-step selection models in periods 1 to T, and $I(t=T)$ is a variable that equals one in period t and zero otherwise. By adopting this methodology, I control for survivorship bias and generate coefficient estimates that are efficient.

3.4 Data

The source of data for this study stems from an anonymous cryptocurrency platform, hereafter referred to as ExchangeX. It encompasses over 1.5 million trade transactions executed by over 15,000 traders within the time frame of June 2017 through December 2018. All trades were executed in the spot cryptocurrency markets, thus no leveraged trades or derivatives, such as futures and options on crypto assets were used. Each trade record consists of details like trade ID, timestamp, trader ID, the asset pair involved, trade direction, volume, counter volume, and the final executed price. The platform facilitates both market and limit orders, which populate the order book and are paired through a matching system. However, a limitation of this data set is its inability to distinguish between these order types. Furthermore, demographic details, like the trader's age and their geographic origin, are also included. These statistics are showcased in Panel A of Table 3.1.

A closer look at account age yields compelling insights about their activity patterns and lifecycle. A key observation is the median account age of just 27 days. This suggests that over half of these accounts exhibit short-lived activity, operating for under a month. The shortest account age recorded is one day, hinting at scenarios where accounts might be established and possibly deserted or terminated within 24 hours due to trial users, unsolicited account creators, or even users who might be discouraged by the platform's offering or experience. Alternatively, heightened marketing or promotions could induce a surge in fresh account establishments. The age average of accounts stands at 101 days, yet the median is only 27 days, indicating a disparity. This variance suggests the coexistence of many short-term accounts alongside a substantive number of longer-lasting ones, which skews the mean.

The age spectrum of traders spans from 20 to 71 years, highlighting the platform's attractiveness to both budding young investors and the seasoned elderly. Predominantly, traders hover around their mid-thirties, potentially indicating an emphasis on amplifying financial returns and broadening their asset portfolios. Those in their late twenties to early thirties likely blend technology adeptness with their trading, leaning into contemporary investment tools. Conversely, individuals aged over 40, extending to 71, could gravitate towards more cautious and enduring investment approaches, valuing financial security and prudence.

In terms of asset diversification, a considerable portion of traders seems to restrict their trading activity to just 2 or 3 distinct crypto assets. Such inclination could stem from a myriad of reasons, such as traders' comfort with familiar assets or their susceptibility to gravitate towards popular assets. Factors like information disparity, where abundant data and perceived reduced risks associated with renowned assets, might inspire increased confidence among traders. This could also mirror an inherent hesitation to branch out in an unpredictable market like cryptocurrency. However, a small segment of traders seems to exploit the crypto asset diversity to its fullest, engaging with up to 65 different assets. This could be indicative of a more active profit-seeking strategy, superior knowledge, or perhaps a diversification strategy aimed at risk mitigation and optimising returns. This disparity accentuates the important role of trader education and the inherent benefits of diversifying within crypto trading.

Regarding the number of trades executed, the median, representing 19 trades, suggests over half of the traders opt for a more conservative trading frequency. Potential explanations could range from risk aversion, limited capital, a preference for a passive investment approach, or possible deficiencies in trading acumen. This infers that a significant segment of the platform's clientele could benefit from educative tools, conservative investment strategy guidelines, and supportive informational frameworks. Contrarily, a niche segment evidences an impressively heightened trading activity, with up to 50,871 trades. This extreme frequency might be a result of algorithm-based trading, day traders leveraging minute price variations, institutional trading houses managing vast resources, or proficient traders navigating intra-day market intricacies.

When delving into trade volumes, the size exhibits a broad spectrum, oscillating between a small \$1 to a noteworthy \$620,021. Such diversity signifies varied trading behaviours and possibly reflects the financial capacity spectrum of the platform's users. The mean trade size is \$489, yet this might not be a reflection of the typical trader's behaviour. The median, at \$201, offers a more balanced view of the majority's trading volume. The difference between the average and the median underscores the impact of outlier trades that significantly skew the mean. These extreme trades could be due to large transactions executed by wealthy or institutional-level traders.

Next, I calculate first the dollar PnLs and their decomposition into realised and unrealised PnLs. I start with PnLs of market agents on an individual level, then aggregate these PnLs on a daily basis and on a per client basis. The PnLs are expressed in US Dollar terms and provide a very important outlook into the activity and behaviour of traders, especially when decomposed into realised and unrealised components.

However, I can hypothesise that if market participants have different sizes of portfolios, I cannot compare dollar PnLs in scale terms. In order to answer the question whether percentage PnLs should be built, I generate the balances of clients. In the next step I can see that in fact balances are very different, hence I move to the next step of scaling PnLs and calculating the percentage PnLs. First, the balances are built as a product of quantities of assets a trader holds by the prices of these assets. Second, the percentage PnLs (which I further call $ROIs$, as opposed to dollar $PnLs$) for all of types of $PnLs$ above: unrealised, realised and total. The results are in units, not percentages, making them similar to returns.

The calculated returns, called $UnrealisedROI_{USD}$, $RealisedROI_{USD}$, and $TotalROI_{USD}$ are reported in the Panel B of the Table 3.1.

The results are extremely interesting. The average return on inventory $UnrealisedROI_{USD}$ has been significantly positive with a mean of 0.20%. The total return $TotalROI_{USD}$ is on average positive too with a mean of 0.11%. Unrealised PnLs are reported on the total number of days when a trader had positive value in the account. Realised PnLs are reported on the basis of those days, when there were actual trades. Interestingly, the realised component of PnLs $RealisedROI_{USD}$ has been negative with an average of a mean of -0.75% and median of -0.45%, that tells us that on average market participants do not exhibit skill.

3.5 Results

3.5.1 Does a trader's past performance affect trade size?

To investigate whether crypto traders exhibit the gambler's fallacy, I examine the relationship between their past performance and their future trade size. The idea is that those who exhibit the gambler's fallacy are likely to increase their trade size after experiencing poor past performance. The results of this analysis are presented in Table 3.2. For Model 1.a, I find negative and statistically significant coefficients of -0.099 and -0.057 for $TotalROI_{t-1}$ and $TotalROI_{t-2}$, respectively. This suggests that traders who perform poorly (i.e. those who experience a negative total return on investment) are more likely to increase their future trade size, and this effect is stronger for the more recent lagged ROI. This finding means that crypto traders are prone to the gambler's fallacy and adopt a martingale betting system as they increase their exposure on future trades to try and make up for poor past performance, since they expect that their subsequent trade will be in line with the market. Note that the $TotalROI$ parameter captures both realised and unrealised profits, and thus may not give an accurate indication of a trader's performance due to active decisions. As such, I run Model 1.b, which uses the realised component of profits due to active trading, to better assess the relationship between a trader's future position size and their past performance due to active trading decisions. Similar to the previous model, I find negative and statistically significant coefficients of -0.053 and -0.038 for $RealisedROI_{t-1}$ and $RealisedROI_{t-2}$, respectively. This reinforces the earlier finding that traders who perform poorly, particularly due to their active trading decisions, are likely to increase their future position size. Moreover, this effect is greater for the more recent period. Again, this suggests that crypto traders exhibit the gambler's fallacy as they increase future trade sizes subsequent to poor performance, in hopes of recovering their past losses as they believe that their next trade will be in line with the market.

Both Models 1.a and 1.b use the return on investment (ROI) as a measure of performance, which captures the overall absolute performance of a trader. In the following models, I use the success ratio (SR) of a trader to measure another aspect of trading performance, which is related to how consistent an individual is in terms of executing profitable trades. In essence, the SR is simply a dichotomised version of the ROI, and aims to measure the proportion of profitable periods or trades relative to the total. Model 1.c shows that the relation between the past success ratios based on total ROI is inversely proportional to the size of future positions, as indicated by the negative coefficients of -0.016 and -0.007 for the $TotalSR_{t-1}$ and $TotalSR_{t-2}$ parameters, respectively. This means that the lower the proportion of profitable periods experienced by the trader, the higher the size of their future position. Again, this effect is greater for the more recent lagged period and is in line with the results mentioned above. Furthermore, I conduct a similar analysis on the SR based on the realised component of the ROI and find coherent results, with negative coefficients of -0.005 and -0.002 for the $RealisedSR_{t-1}$ and $ReaslisedSR_{t-2}$ parameters, respectively. While these coefficients are negative and statistically significant, suggesting evidence of the gambler's fallacy among crypto traders, they are smaller in magnitude compared to those reported for the $TotalSR$ parameters. This means that traders react more strongly — in terms of changes in future trade size — to changes in their overall portfolio value compared to value changes arising from to their own trading activity. Moreover, this implies that traders, to a much larger extent, bet on reversal patterns in the direction of the market, rather than reversals in their own trading abilities.

With respect to the control variables, I find negative coefficients for the lagged $log(Volume)$ parameters across all models, with values ranging between -0.068 and -0.065 for $log(Volume)_{t-1}$ and between -0.054 and -0.048 for $log(Volume)_{t-2}$. This means that there is a negative autocorrelation between past and future trade sizes. This finding is in line with what is discussed above, as traders with poor past performance and who are trading a certain position size are likely to increase that position in the future to compensate for their historically incorrect trades. Nonetheless, I find no significant relation across all models for the $log(AverageTrade)$ parameter, which is estimated as a cumulative rolling average of a trader's trade size. This may be due to traders constantly changing their subsequent position size in response to their past performance rather than sticking with a rather constant trade size. Such a finding further supports evidence of the gambler's fallacy, as traders do not adopt a static notional trade size value, but instead alter it according to their past performance. With respect to $log(AverageBalance)$, I find positive and statistically significant coefficients across all models ranging between 0.002 and 0.006, which naturally means that those with larger average balances are more likely to have bigger trade sizes. I report negative yet small coefficients for the $NumberTrades$ parameter across all models, implying that the more individuals trade, the lower their subsequent trade size, which may be due to these traders losing wealth over time. Such a finding parallels the evidence in the literature on the relationship between trading and wealth (Barber & Odean 2000). Similarly, the coefficients for $NumberMarkets$ are also negative across all models, which means that the wider the investment universe of a trader, the more thinly-spread their wealth is across multiple markets. Regarding the market volatility parameter, I find that the contemporaneous volatility is positively associated with trade size, as individuals increase their exposures to take advantage of larger market swings. However, the lagged $Volatility_{t-1}$ parameter has a weak negative statistical significance while $Volatility_{t-2}$ has a negative correlation with future trade size. This suggests that traders subsequently decrease their trade sizes after having already increase their exposures during the volatile period. With respect to trader age, I find that those in the age group between 30 and 40 years are more likely to have larger position sizes, as indicated by the positive coefficients of 0.053 and 0.055 for Models 1.b and 1.d, respectively. Hence, this age group may be generally wealthier and more prone to taking risks compared to their younger counterparts (i.e. age group 18 to 30 years), which is then translated into larger position sizes. I do not find any statistically significant relationships for age groups (40, 50] and (50, 60]. Nevertheless, I report negative coefficients ranging between -0.149 and -0.135 across all models for age group (60+], which suggests that this particular group has generally less exposure to crypto, which may be due to their lower level of comfort with this novel asset class. Finally, with respect to traders' geographical location, I find positive coefficients for all continent variables for Models 1.b and 1.d — note that Africa is taken as the base category. Specifically, I find larger coefficients for traders located in Oceanian and Asian countries compared to those located in Africa, America, and Europe, which may be due to their greater degree of wealth and higher exposure to the crypto asset class.

The models in Table 3.2 use the natural logarithm of the dollar amount of trades as the dependent variable. While the previous analysis allows us to examine how past performance is associated with the size of future trades, it does not allow us to examine if traders increase (or decrease) their position sizes relative to their own baseline or average. In order to do so, I run the models again; however, I use the binary dependent variable $D(Volume)$ which takes the value of one if the trade size at time t is larger than the rolling average trade size over the period $t-1$ and $t-q$, where q equals five. Table 3.3 presents the results.

For Model 2.a, I find negative and statistically significant coefficients of -0.112 and -0.06 for $TotalROI_{t-1}$ and $TotalROI_{t-2}$, respectively. This corroborates what I found in the previous analysis, and implies that those who experience negative past performance are likely to increase the size of their subsequent trade to an amount that is larger than their baseline average trade size. This effect is also larger for the more recent lagged ROI and suggests that crypto traders exhibit the gambler's fallacy with a trading pattern that resembles a martingale betting system. To segregate the realised component of returns from the total returns, I run Model 2.b and find statistically significant coefficients of -0.091 and -0.038 for $RealisedROI_{t-1}$ and $RealisedROI_{t-2}$, respectively. Again, this parallels the evidence presented in the previous analysis that those who have poor past performance are likely to trade larger amounts that exceed their average baseline trade size. Consequently, this implies that crypto traders exhibit the gambler's fallacy, such that they increase the size of their future trade sizes in order to make up for poor past performance, assuming that their luck is going to turn around and make up for their past losses.

Next, I run Models 2.c and 2.d, which include the SR of traders instead of the ROI, in order to capture the effect of consistency in performance on the likelihood of a trader changing their position size relative to their baseline. I find that the lagged historical $TotalSR$ parameters have a significant and negative effect on the likelihood of traders increasing their trade size. This suggests that those with a lower historical proportion of profitable trades exhibit an increase in their subsequent trade sizes. I also report similar results for the $RealisedSR_{t-1}$ and $RealisedSR_{t-2}$ parameters with coefficients of -0.037 and -0.028, respectively. Again, these findings support the argument that crypto traders exhibit the gambler's fallacy as they increase the size of their trades given poor realised past performance.

In contrast to the previous analysis, I include as control variables the lags of the $D(Volume)$ instead of $log(Volume)$. I find positive coefficients between 0.33 and 0.378 for $D(Volume)_{t-1}$ and between 0.257 and 0.295 for $D(Volume)_{t-2}$, which imply that there is some momentum in the way traders increase their exposure over subsequent trades. This is in line with what is reported for $log(Volume)$ in the previous models, as traders with negative (positive) past performance and a certain baseline position size are likely to increase (decrease) the size of future trades. Similar to the previous analysis, I find no significant effects for the $log(AverageTrade)$ parameter, suggesting that traders regularly change their position size in relation to the baseline trade size rather than sticking with a constant dollar amount. Regarding the $log(AverageBalance)$ variable, I find positive and statistically significant coefficients across all models ranging between 0.013 and 0.016. This parallels my previous findings and suggests that traders with larger average balances are more likely to increase the size of their future trade sizes in relation to their baseline. With respect to the $NumberTrades$ parameter, I report negative but small coefficients for all models. This suggests that the larger the number of trades executed, the smaller the size of future trade sizes, which may be due to traders losing wealth over time. I also report negative coefficients for the $NumberMarkets$ variable, which corroborates my earlier results, indicating that the wider a trader's investment universe, the smaller the trade sizes they are able to allocate per market. Moreover, I find that contemporaneous volatility is positively related to the likelihood of a trader increasing their trade size relative to their baseline as they aim to take advantage of larger market movements. Nonetheless, the lagged volatility parameters have negative coefficients meaning that traders decrease their position size relative to their baseline following periods of high volatility. I report that those in the age group between 30 and 40 years are more likely to increase their position sizes relative to their baseline sizes, as indicated by the positive coefficients of 0.054 for Models 2.b and 2.d, respectively. This suggests that these traders are relatively wealthier than their younger counterparts and thus are able to take on greater exposures to cryptocurrencies. Moreover, I find negative coefficients across all models for age group (60+], which again implies that these individuals have less of an appetite for crypto investments. Finally, regarding geographical location, I find results similar to the initial analysis, whereby I report larger coefficients for traders located in Oceania and Asia compared to those in Africa, America, and Europe. This, again, may be due to the greater amount of wealth that is allocated to cryptocurrencies within these regions.

3.5.2 Does a trader's past performance affect net crypto exposure?

The above analysis focuses on the relation between past performance and the size of future trades. As an alternative to assessing the gambler's fallacy among crypto traders, I examine the impact of past trader performance on the net crypto exposure of traders. The results for the regression models in Section 3.3.2 are presented in Table 3.4.

For Model 3.a, I find positive and statistically significant coefficients of 0.02 and 0.013 for $TotalROI_{t-1}$ and $TotalROI_{t-2}$, respectively. This implies that traders who have positive past total returns are more likely to exhibit a greater net exposure to crypto assets in the future. This effect is larger for the more recent lagged ROI. These results may simply be due to the trader having a certain crypto exposure, and thus as market prices increase, this translates into a higher $TotalROI$ and a subsequently larger proportion of the trader's portfolio being in crypto. As mentioned in the previous analyses, $TotalROI$ measures both realised and unrealised profits, thus I run Model 3.b, which uses the realised component of profits due to active trading to better estimate the effect of a trader's past performance due to active decisions on their future net crypto exposure. The coefficients for the $RealisedROI_{t-1}$ and $RealisedROI_{t-2}$ are negative and equal to -0.011 and -0.0101, respectively. This supports the notion that crypto traders are prone to the gambler's fallacy as they increase their exposure to crypto to try and make up for past poor performance as they expect that a larger exposure will compensate for their sub-optimal past decisions. Again, I find that this effect is greater for the more recent lagged realised return.

Both Model 3.a and Model 3.b use ROI as a measure of performance, which estimates the overall absolute performance of a trader, thus I also use the success ratio (SR) to examine the relation between a trader's consistency in executing profitable trades and their net crypto exposure. The results of Model 3.c show positive coefficients of 0.023 and 0.01 for the $TotalSR_{t-1}$ and $TotalSR_{t-2}$ parameters, respectively, which again could be explained by the trader having a crypto exposure that increases simply due to rising crypto prices. Thus, to isolate the impact of market prices from trader decisions, I run Model 3.d, which uses the SR based on the realised component of profits and find negative coefficients of -0.014 and -0.011 for the $RealisedSR_{t-1}$ and $ReaslisedSR_{t-2}$ parameters, respectively. These figures suggest that those who consistently under-perform (as represented by a lower SR) exhibit higher net crypto exposure, which could be an indication of the gambler's fallacy as these traders aim to increase net exposure to make up for past sub-optimal decisions as they bet on reversal patterns in the direction of the market, rather than reversals in their own trading abilities.

Regarding the control variables, I find negative coefficients for the lagged $\%(CryptoExposure)$ parameters across all models, with values around -0.0172 for the $\%(CryptoExposure)_{t-1}$ variable and around -0.005 for the $\%(CryptoExposure)_{t-2}$ variable. This suggests that there is a negative autocorrelation between past and future net crypto exposure, which could be explained by traders increasing their exposures through active trading every time the market drops, which results in a lower net crypto exposure. This echoes the above-mentioned results related to the parameters based on the realised component of profit, and further supports the notion of the gambler's fallacy among crypto traders as they increase exposure subsequent to low past exposure. I find positive coefficients across all models for the $log(AverageTrade)$ parameter, which is estimated as a cumulative rolling average of a trader's trade size. This suggests that traders with a larger average trade size exhibit greater net crypto exposure, which is logical as these users allocate bigger dollar amounts to this novel asset class. Nonetheless, I do not find a similar relation when it comes to the $log(AverageBalance)$, which means that the overall degree of trader wealth does not impact the composition of their portfolio. In other words, all traders regardless of their wealth, as proxied by the size of their balance, have the same affinity towards risk and towards holding the same proportion of crypto assets in their portfolios. With respect to the number of trades, I find positive coefficients of around 0.008 for the $NumberTrades$ parameter across all models, which suggests that those who trade more are likely to hold more crypto in their portfolios. It follows that those who trade frequently are more likely to be going long on crypto as an asset class, thus accumulating a larger exposure over time. Similarly, the coefficients for $NumberMarkets$ are also positive across all models, suggesting that the wider the investment universe of a trader, the greater their net crypto exposure as their diversify across a wider range of crypto assets. With respect to market volatility, I find that the contemporaneous volatility is positively related to net crypto exposure, as individuals increase their exposures to take advantage of larger market swings. However, the lagged $Volatility_{t-1}$ and $Volatility_{t-2}$ parameters have a small negative effect on crypto exposure, suggesting that traders experience a small decline in their crypto exposure subsequent to highly volatile market periods, which may be a result of falling crypto prices. Regarding trader age, I find that those in the age group between 30 and 40 years are more likely to have larger net crypto exposures, as indicated by the positive coefficients between 0.0225 and 0.023 across all models. This suggests that this age group may be generally wealthier and more prone to taking risks compared to their younger counterparts (i.e. age group 18 to 30 years), which results in larger net crypto exposures. I do not find any significant effects for age groups (40, 50] and (50, 60]. However, I find negative coefficients of around -0.0078 across all models for age group (60+]. This means that this particular group has generally less exposure to crypto, which may be due to their lower level of comfort with this novel asset class. Finally, regarding geographical location, I find positive coefficients for Asian and European $Continent$ variables across all models — note that Africa is taken as the base category, with coefficients for $Continent_{Asia}$ being generally higher and around 0.0477 relative to $Continent_{Europe}$ which are around 0.032. This suggests that traders located in Asia and Europe are more likely to hold larger crypto exposures relative to those based in the Americas, Oceania, and Africa, which may be due to their greater degree of wealth and accessibility to the crypto asset class.

3.5.3 Do market trends impact trade direction?

In this analysis, I investigate whether, and to what extent, past market trend directions impact the direction of an individual's trade. The results of Model 4 are reported in Table 3.5. The coefficients for all five lagged $Trend_{t-q}$ parameters are negative and statistically significant. This means that when the market was trending in one direction, traders subsequently traded in the opposite direction, implying that they expect the market to change direction following their trades. Such a pattern supports the argument that traders exhibit the gambler's fallacy as they believe that the market should and will change direction. Consequently, crypto traders in this sample bet on market reversals and mean reversion trends. I also note that this effect is largest (albeit negative) for the more recent $Trend$ lags, and decays logarithmically towards zero the further back the lag. Hence, traders are likely to react more strongly to more recent market trend movements and bet in the direction opposite to how the market is trending.

3.6 Conclusion

This paper investigates whether and how past performance impacts future trader decisions in the cryptocurrency market. Specifically, I examine whether traders exhibit the gambler's fallacy, whereby poor past performance results in traders increasing their subsequent trade size in order to make up for their sub-par performance.

To investigate this, I use a proprietary data set from an anonymous cryptocurrency exchange, which I call ExchangeX, which comprises of more than 1.5 million trades executed by over 15,000 traders from June 2017 to December 2018. The findings reveal that traders have a tendency towards the gambler's fallacy; traders with poor active past performance tend to increase their future net exposure, possibly in an attempt to recover losses. This pattern is also evident when analysing the success ratio, where traders with consistently poor performance increase their net exposure. Control variables indicate that larger average trade sizes lead to greater net exposure, but overall wealth does not affect portfolio composition. Furthermore, frequent trading and investment in a broader range of markets correlate with higher net crypto exposure. Market volatility positively influences net exposure, with traders looking to capitalise on large market movements. Demographically, traders aged 30-40 are more likely to increase their crypto exposure, while those over 60 show less exposure, potentially due to lower familiarity with the asset class. Geographically, traders in Asia and Europe tend to have larger exposures compared to other continents. Finally, traders are likely to trade in the direction opposite to how the market has been trending.

These results support the prevalence of the gambler's fallacy among cryptocurrency traders, whereby individuals are likely to increase their trade size after experiencing poor past performance as they aim to make up for poor past decision. Moreover, cryptocurrency traders believe in a mean reversion pattern, as they bet that the most recent market trending will reverse following their subsequent trade.

These findings are of importance to the academic audience as well as to individual cryptocurrency traders, as they highlight the tendency of traders to succumb to the gambler's fallacy, which has been documented to negatively impact trader performance. By learning about this behavioural pattern, one can work towards avoiding making decisions based on short-term market trends and instead invest based on information that aims to capture the value of the underlying technology.

This paper is not without its limitations. First, while this study uses a unique data set of transactions from June 2017 to December 2018 that allows us to conduct a micro-level analysis of trader performance and behaviour, the cryptocurrency environment has changed significantly since then with the rise of DeFi and decentralised exchanges. Hence, I encourage researchers to conduct a similar analysis on a more up-to-date data set to check whether the behavioural bias found in this study persists in other venues within the crypto space. Second, while my analysis investigates how traders exchange crypto to fiat and vice versa, the complexity of cryptocurrency trading — traders do not have to trade into fiat when exchanging one cryptocurrency for another — calls for the development of more sophisticated models to capture the transitions not only between crypto and fiat, but also within each of these money categories.

Table 3.1: Descriptive Statistics and Performance Measures of ExchangeX from June 2017 to December 2018. The following table shows descriptive statistics of traders on ExchangeX, as well as information on return on investment (ROI) for traders on the platform. *Age of the Account* is the life of the account, *Age* is the age of the trader.
Number of Assets Traded is the number of assets the trader has used, *Number of Trades* is the number of trades filled and *Size of the Trade, USD* is the average size of a trade. *ROI* shows the performance of market participants. $ROI_{Unrealised}$ is the return component, which reflects the holding of inventory. $ROI_{Realised}$ is the component that captures active portfolio management skills of a trader. ROI_{Total} is the sum of two components above. All *ROI* metrics are in US dollars and on a daily basis.

Panel A: Trader Descriptive Statistics						
	Min.	**1st Q.**	**Mean**	**Median**	**3rd Q.**	**Max.**
Age of the Account, days	1	4	101	27	188	545
Age, years	20	29	37	34	41	71
Number of Assets Traded	2	2	3	3	3	65
Number of Trades	1	8	91	19	29	50,871
Size of the Trade, USD	1	14	489	201	409	620,021
Panel B: ROI Metrics						
ROI˙Unrealised, USD	-16.22%	-0.82%	0.23%	0.16%	0.56%	16.44%
ROI˙Realised, USD	-8.54%	-1.69%	-0.76%	-0.45%	0.18%	5.98%
ROI˙Total, USD	-16.22%	-0.67%	0.11%	0.16%	0.49%	15.26%

Table 3.2: Trade size. The following table shows the results of Models 1.a, 1.b, 1.c, and 1.d. The dependent variable is the $log(Volume)$, which is the natural logarithm of the dollar value of transactions executed by trader. The independent variables that measure performance include the total ROI, given by $TotalROI$, the realised ROI, $RealisedROI$, as well as the total and realised ROI, given by $TotalSR$ and $RealisedSR$, respectively. $log(Volume)_{t-1}$ is the lagged dependent variable. Moreover, I include control variables for each trader that are estimated up to but not including time t such as the natural logarithm of the average trade size, $log(AverageTrade)$, natural logarithm of the average balance size, $log(AverageBalance)$, cumulative number of trades executed, $NumberTrades$, number of unique markets traded, $NumberMarkets$, and market volatility, $Volatility$, proxied by the standard deviation of hourly returns of the BTC-USD market. I control for demographics such as geographical, given by $Continent$, and age, denoted as Age. All models are augmented with trader and time fixed effects.

	Model (1.a)	Model (1.b)	Model (1.c)	Model (1.d)
$TotalROI_{t-1}$	-0.099^***(0.025)			
$TotalROI_{t-2}$	-0.057^***(0.023)			
$RealisedROI_{t-1}$		-0.053^***(0.012)		
$RealisedROI_{t-2}$		-0.038^***(0.011)		
$TotalSR_{t-1}$			-0.016^***(0.003)	
$TotalSR_{t-2}$			-0.007^***(0.002)	
$RealisedSR_{t-1}$				-0.005^***(0.002)
$RealisedSR_{t-2}$				-0.002^**(0.001)
$log(Volume)_{t-1}$	-0.068^***(0.004)	-0.065^***(0.005)	-0.068^***(0.004)	-0.065^***(0.005)
$log(Volume)_{t-2}$	-0.054^***(0.004)	-0.048^***(0.004)	-0.054^***(0.004)	-0.048^***(0.004)
$log(AverageTrade)$	-0.001(0.001)	-0.001(0.001)	-0.001(0.001)	-0.00003(0.001)
$log(AverageBalance)$	0.002^**(0.001)	0.006^***(0.002)	0.002^**(0.001)	0.005^***(0.002)
$NumberTrades$	−0.00004*** (0.00002)	−0.00004*** (0.00002)	−0.00003* (0.00002)	−0.00003* (0.00002)
$NumberMarkets$	-0.023^***(0.001)	-0.026^***(0.001)	-0.023^***(0.001)	-0.027^***(0.001)
$Volatility_t$	0.001^***(0.0001)	0.001^***(0.0001)	0.001^***(0.0001)	0.001^***(0.0001)
$Volatility_{t-1}$	-0.0003^***(0.0001)	-0.00003(0.0001)	-0.0002^*(0.0001)	-0.0001(0.0001)
$Volatility_{t-2}$	-0.001^***(0.0001)	-0.001^***(0.0001)	-0.001^***(0.0001)	-0.001^***(0.0001)
$Age_{(30,40]}$	0.031(0.019)	0.053^**(0.023)	0.030(0.019)	0.055^**(0.022)
$Age_{(40,50]}$	-0.027(0.023)	-0.022(0.025)	-0.024(0.024)	-0.021(0.026)
$Age_{(50,60]}$	-0.044(0.032)	-0.017(0.033)	-0.042(0.035)	-0.017(0.036)
$Age_{(60+]}$	-0.147^***(0.051)	-0.135^**(0.062)	-0.149^***(0.051)	-0.136^**(0.062)
$Continent_{Americas}$	0.074(0.071)	0.187^**(0.086)	0.082(0.072)	0.185^**(0.088)
$Continent_{Asia}$	0.092(0.068)	0.198^**(0.080)	0.086(0.072)	0.191^**(0.081)
$Continent_{Europe}$	0.064(0.063)	0.162^**(0.074)	0.081(0.064)	0.162^**(0.077)
$Continent_{Oceania}$	0.061(.077)	0.232** (0.096)	0.068(0.076)	0.228** (0.093)
N	67,052	48,190	67,052	48,190
R^2	0.537	0.547	0.537	0.547
Adjusted R^2	0.453	0.467	0.453	0.467

Note: *p<0.1; **p<0.05; ***p<0.01

Table 3.3: Dichotomous trade size. The following table shows the results of Models 2.a, 2.b, 2.c, and 2.d. The dependent variable is the binary parameter $D(Volume)$, which takes the value of one if the trade size at time t is larger than the rolling average trade size over a five-period window. The independent variables that measure performance include the total ROI, given by $TotalROI$, the realised ROI, $RealisedROI$, as well as the dichotomised parameters of the total and realised ROI, given by $TotalSR$ and $RealisedSR$, respectively. The $D(Volume)_{t-q}$ parameter is the lagged dependent variable. Moreover, I include control variables for each trader that are estimated up to but not including time t such as the natural logarithm of the average trade size, $log(AverageTrade)$, natural logarithm of the average balance size, $log(AverageBalance)$, cumulative number of trades executed, $NumberTrades$, number of unique markets traded, $NumberMarkets$, and market volatility, $Volatility$, proxied by the standard deviation of hourly returns of the BTC-USD market. I control for demographics such as geographical, given by $Continent$, and age, denoted as Age. All models are augmented with trader and time fixed effects.

	Model (2.a)	Model (2.b)	Model (2.c)	Model (2.d)
$TotalROI_{t-1}$	−0.112*** (0.032)			
$TotalROI_{t-2}$	−0.06*** (0.022)			
$RealisedROI_{t-1}$		−0.091*** (0.02)		
$RealisedROI_{t-2}$		−0.038*** (0.011)		
$TotalSR_{t-1}$			−0.016*** (0.005)	
$TotalSR_{t-2}$			−0.014*** (0.003)	
$RealisedSR_{t-1}$				−0.037*** (0.010)
$RealisedSR_{t-2}$				−0.028*** (0.010)
$D(Volume)_{t-1}$	0.330*** (0.016)	0.376*** (0.019)	0.330*** (0.016)	0.378*** (0.019)
$D(Volume)_{t-2}$	0.258*** (0.016)	0.295*** (0.019)	0.257*** (0.016)	0.294*** (0.019)
$log(AverageTrade)$	-0.001(0.001)	-0.001(0.001)	-0.001(0.001)	-0.00003(0.001)
$log(AverageBalance)$	0.013*** (0.001)	0.015*** (0.002)	0.013*** (0.001)	0.016*** (0.002)
$NumberTrades$	−0.0002*** (0.00003)	−0.0001*** (0.00003)	−0.0002*** (0.00003)	−0.0002*** (0.00003)
$NumberMarkets$	-0.030^***(0.002)	-0.027^***(0.002)	-0.030^***(0.002)	-0.027^***(0.002)
$Volatility_t$	0.001^***(0.0001)	0.001^***(0.0001)	0.001^***(0.0001)	0.001^***(0.0001)
$Volatility_{t-1}$	-0.001^***(0.0001)	-0.0003^*(0.0001)	-0.001^***(0.0001)	-0.0003^*(0.0001)
$Volatility_{t-2}$	-0.001^***(0.0001)	-0.001^***(0.0001)	-0.001^***(0.0001)	-0.001^***(0.0001)
$Age_{(30,40]}$	0.030(0.019)	0.054^**(0.023)	0.030(0.019)	0.054^**(0.023)
$Age_{(40,50]}$	-0.029(0.025)	-0.021(0.029)	-0.029(0.025)	-0.022(0.029)
$Age_{(50,60]}$	-0.047(0.033)	-0.013(0.039)	-0.046(0.033)	-0.014(0.039)
$Age_{(60+]}$	-0.147^***(0.051)	-0.135^**(0.062)	-0.149^***(0.051)	-0.136^**(0.062)
$Continent_{Americas}$	0.074(0.071)	0.185^**(0.090)	0.080(0.071)	0.184^**(0.090)
$Continent_{Asia}$	0.088(0.063)	0.196^** (0.081)	0.093(0.063)	0.192^** (0.081)
$Continent_{Europe}$	0.064(0.061)	0.164^**(0.078)	0.070(0.061)	0.160^**(0.078)
$Continent_{Oceania}$	0.059(.077)	0.230** (0.097)	0.067(0.077)	0.227** (0.097)
Observations	67,052	48,190	67,052	48,190
Log Likelihood	-44,504.510	-31,735.000	-44,520.150	-31,741.760
Akaike Inf. Crit.	89,051.030	63,511.990	89,082.300	63,525.510
Adjusted R^2	0.574	0.533	0.536	0.498

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table 3.4: Net crypto exposure. The following table shows the results of Models 1.a, 1.b, 1.c, and 1.d. The dependent variable is the $\%(CryptoExposure)$, which is the proportion of a trader's account that is in crypto instead of fiat. The independent variables that measure performance include the total ROI, given by $TotalROI$, the realised ROI, $RealisedROI$, as well as the total and realised ROI, given by $TotalSR$ and $RealisedSR$, respectively. $\%(CryptoExposure)_{t-q}$ is the lagged dependent variable. Moreover, I include control variables for each trader that are estimated up to but not including time t such as the natural logarithm of the average trade size, $log(AverageTrade)$, natural logarithm of the average balance size, $log(AverageBalance)$, cumulative number of trades executed, $NumberTrades$, number of unique markets traded, $NumberMarkets$, and market volatility, $Volatility$, proxied by the standard deviation of hourly returns of the BTC-USD market. I control for demographics such as geographical, given by $Continent$, and age, denoted as Age. All models are augmented with trader and time fixed effects.

	Model (3.a)	Model (3.b)	Model (3.c)	Model (3.d)
$TotalROI_{t-1}$	0.02*** (0.001)			
$TotalROI_{t-2}$	0.013*** (0.0008)			
$RealisedROI_{t-1}$		−0.011*** (0.001)		
$RealisedROI_{t-2}$		−0.0101*** (0.001)		
$TotalSR_{t-1}$			0.023*** (0.005)	
$TotalSR_{t-2}$			0.01*** (0.003)	
$RealisedSR_{t-1}$				−0.014*** (0.002)
$RealisedSR_{t-2}$				−0.011** (0.001)
$\%(CryptoExposure)_{t-1}$	−0.017*** (0.003)	−0.0172*** (0.003)	−0.0174*** (0.003)	−0.0173*** (0.003)
$\%(CryptoExposure)_{t-2}$	−0.005*** (0.001)	−0.005*** (0.001)	−0.005*** (0.001)	−0.005*** (0.001)
$log(AverageTrade)$	0.002*** (0.0001)	0.0019*** (0.0001)	0.0019*** (0.0001)	0.0019*** (0.0001)
$log(AverageBalance)$	0.0001 (0.0001)	0.0001 (0.0001)	0.0001 (0.0001)	0.0001 (0.0001)
$NumberTrades$	0.008*** (0.0003)	0.008*** (0.0003)	0.008* (0.0003)	0.008* (0.0003)
$NumberMarkets$	0.0144*** (0.001)	0.0143*** (0.001)	0.0143*** (0.001)	0.0141*** (0.001)
$Volatility_t$	0.001*** (0.0001)	0.001*** (0.0001)	0.001*** (0.0001)	0.001*** (0.0001)
$Volatility_{t-1}$	−0.0003*** (0.0001)	−0.00002** (0.0001)	−0.0002** (0.0001)	−0.0002** (0.0001)
$Volatility_{t-2}$	−0.0003*** (0.0001)	−0.0002** (0.0001)	−0.0002** (0.0001)	−0.0002** (0.0001)
$Age_{(30,40]}$	0.023*** (0.004)	0.0225*** (0.004)	0.0226*** (0.004)	0.0225*** (0.004)
$Age_{(40,50]}$	0.007(0.005)	0.007(0.005)	0.0068(0.005)	0.0069(0.005)
$Age_{(50,60]}$	-0.0078(0.006)	-0.0079(0.006)	-0.0078(0.006)	-0.0076(0.006)
$Age_{(60+]}$		-0.085^***(0.004)	−0.0847*** (0.004)	−0.0845*** (0.004)
−0.0844*** (0.004)				
$Continent_{Americas}$	0.024(0.02)	0.025 (0.02)	0.025(0.02)	0.024 (0.02)
$Continent_{Asia}$	0.0478*** (0.019)	0.0477*** (0.019)	0.0476*** (0.019)	0.0476*** (0.019)
$Continent_{Europe}$	0.032*** (0.012)	0.0321*** (0.012)	0.0321*** (0.012)	0.0319*** (0.013)
$Continent_{Oceania}$	0.041(0.063)	0.048 (0.062)	0.042(0.062)	0.045 (0.063)
N	67,052	48,190	67,052	48,190
R^2	0.585	0.562	0.597	0.534
Adjusted R^2	0.492	0.47	0.488	0.465

Note: *p<0.1; **p<0.05; ***p<0.01

Table 3.5: Gambler's Fallacy - Trade direction. The following table shows the results of Model 4. The dependent variable, *Direction*, is a binary variable that takes the value of one if the trader exchanges fiat to crypto, and zero if the trader exchanges crypto to fiat. The independent variables include five lags of the market trend direction, given by $Trend_{t-q}$, which are equal to one if the general crypto market is trending upwards, and zero if downwards. The model is augmented with trader, asset, and time fixed-effects. I also report the number of observations, N, as well as the pseudo R^2.

	Model 4
$Trend_{t-1}$	-0.043^***(0.007)
$Trend_{t-2}$	-0.024^***(0.007)
$Trend_{t-3}$	-0.0192^***(0.007)
$Trend_{t-4}$	-0.018^***(0.007)
$Trend_{t-5}$	-0.014^**(0.007)
N	1,270,655
Pseudo R^2	15.23%
Note:	*p<0.1; **p<0.05; ***p<0.01

Chapter 4

The Impact of Sentiment on Trader Performance and Activity in the Cryptocurrency Market

Chapter 4

The Impact of Sentiment on Trader Performance and Activity in the Cryptocurrency Market

4.1 Introduction

Cryptocurrencies have gained tremendous popularity in recent years and have thus generated significant amounts of talk, both offline and online. These discussions have become crucial when it comes to determining the value of cryptocurrencies and the level of engagement among market participants, especially given the lack of a traditional quantifiable fundamentalist approach to valuation (Gurdgiev & O'Loughlin 2020). Moreover, as the technology underlying cryptocurrencies continues to develop, there is little consistent historical precedence for pricing behaviour. Thus, the cryptocurrency market remains somewhat ambiguous in terms of identifiable fundamental factors that can be used to determine value. Some researchers (Treiblmaier 2022) believe that cryptocurrencies have no fundamental value, so, without anchoring to the fundamental value, sentiment may play a critical role. Consequently, this has motivated researchers to look for other indicators, which can help explain the price dynamics of cryptocurrency markets.

Many studies have presented evidence supporting the notion that financial markets are affected by news, and that news impacts market sentiment Peterson (2016). In the crypto market specifically, Shiller (2020) argues that the value of cryptocurrencies, such as Bitcoin, is driven by public excitement. Hence, discussions about cryptocurrency valuations are often based on speculative scenarios and opinions. Studies have found that opinions published online through social media platforms have a significant impact on cryptocurrency prices (Kristoufek 2013, Shen et al. 2019, Kraaijeveld & De Smedt 2020, Naeem, Mbarki, Suleman, Vo & Shahzad 2021, Naeem, Mbarki & Shahzad 2021). As such, researchers have focused on text-based sentiment via social media platforms, including *Reddit* (Nasekin & Chen 2020) and *Twitter* (Guégan & Renault 2020), to investigate price discovery in the crypto market. The evidence from these studies are in line with what the crypto market has experienced in terms of explosive appreciation in prices, especially for "meme" coins, which do not have any identifiable fundamental factors but have generated returns that dwarf those found in equity markets as well as the largest cryptocurrencies, Bitcoin and Ethereum included.[1] Specifically,

[1]Dogecoin, which is a peer-to-peer cryptocurrency depicting a dog was launched in 2013 as a sarcastic digital asset. Over a period of twenty-four hours, Dogecoin appreciated by 800% against USD, which is a unique event that has been attributed to the coordinated actions of retail investors facilitated by the Reddit platform (Kharpal 2021).

these studies have shown that price movements and trends in the crypto market, while they cannot be explained by any identifiable fundamental factors, are driven by market sentiment as captured through blog posts and opinions published on social media platforms.

The literature on sentiment analysis in the crypto market has primarily focused on text-based models based on social media posts to predict the direction and volatility of price returns. Despite the evidence presented in the literature on the impact of sentiment on cryptocurrency prices, very little research has been done on the effects of sentiment on decision making at the individual trader level. Hence, I take this opportunity to fill this gap by investigating the degree to which market sentiment affects the performance, trade size, as well as the frequency of trading among crypto traders. Specifically, I use a unique data set of over 1.5 million transactions executed by over 15,000 traders on an anonymous cryptocurrency exchange. Most studies on the cryptocurrency market have used text-based measures of sentiment using data from social media platforms, such as Twitter or Reddit, implying a very strong association between crypto traders and their use of social media platforms. In other words, these studies suggest that crypto traders are active users of social media platforms and are highly likely to be impacted by the news and opinions published on these platforms.

To avoid making this assumption, I adopt an alternative measure called the Net Unrealised Profit/Loss (or NUPL), which captures the difference between the on-chain cost basis and market value of digital assets on a blockchain network. Specifically, the on-chain cost basis takes the price of each digital asset at the time it last moved on the blockchain (i.e. the time it moved from one digital wallet to another), which is then averaged and multiplied by the total number of coins in circulation. The market value, on the other hand, takes the current price of the digital asset multiplied by the number of coins in circulation. By looking at the difference between the price when a transaction happened on the blockchain and the current price, one can determine whether and what proportion of the coins on the network are in a current state of unrealised profit or loss. In other words, NUPL is an accounting measure that compares the contemporary value of the blockchain, given by the market price, relative to its cost basis on-chain (i.e. the cost of the coin when it was last moved on the blockchain). A positive (negative) value suggests that the blockchain network is in a state of profit (loss), and the further the NUPL deviates from zero, the more likely the market is reaching a top or bottom. When a growing proportion of coins on a network begin to carry an increasing unrealised profit, this suggests a higher level of market sentiment and a greater likelihood that traders will succumb to greed and begin taking profits. Consequently, this results in prices dropping further, thus shifting the network from a state of unrealised gain to unrealised loss. The further the prices drop and the longer they remain low, market sentiment drops to low levels and becomes increasingly governed by a state of capitulation and apathy. While no research, up to my knowledge, has used NUPL as a measure of sentiment, some researchers have investigated the characteristics of this metric (Sakkasa & Urquhart n.d.).

My research presents several findings that highlight the impact of market sentiment on crypto trader performance and trading activity, and contributes to the literature on how market sentiment impacts the decision-making process of traders in a market that is relatively ambiguous in nature.

First, I find that a positive changes in lagged NUPL values lead to an increase in total returns for the trader, suggesting a momentum effect in market prices that is driven by on-chain or blockchain activity.

Second, I focus the analysis on sentiment and performance on the active or realised component of a trader's returns, which is the result of active trading. I find that while positive changes in lagged values of NUPL in the network lead to higher realised returns, this effect though significant is relatively small. This means that traders observe and trade on changes in network value as a way to gauge the direction of the market. Moreover, traders who react immediately to market sentiment, specifically during times of high market sentiment, are likely to realise higher positive returns.

Third, I examine whether and to what extent market sentiment impacts the size of trades, and find that positive changes in net unrealised profits on the network lead to larger future trade sizes. While this may be interpreted as a positive relation between market sentiment and trade size, the fact that a high $NUPL$ value is related to high market prices consequently implies larger trade sizes in terms of U.S. Dollars. To address this, I show that a positive change in market sentiment results in larger trade sizes; hence, traders increase their exposure when market sentiment is rising.

Finally, since the dollar size of a trade is mathematically linked to $NUPL$ — which is calculated using market prices — making it hard to estimate the impact of market sentiment on future trade exposure, I run an alternative analysis where I investigate the impact of market sentiment on changes in trade size. I find no relation between changes in lagged levels of $NUPL$ and changes in trade size. The results suggest that a "change" in trade size is agnostic to market sentiment, and thus traders do not change their exposure according to market sentiment.

The remainder of this paper is divided as follows. Section 4.2 covers the literature about the impact of sentiment in the crypto market. Section 4.3 explains the methodology used in this paper. Section 4.4 outlines the data set used as well as some descriptive statistics. Section 4.5 presents the results and discusses the findings. Finally, Section 4.6 concludes this paper.

4.2 Literature Review

In behavioural economics, Kaplanski & Levy (2010) define sentiment as a misconception that can lead to mispricing of assets. Consequently, sentiment can result in markets becoming highly speculative (Baker & Wurgler 2007), as it becomes more difficult and subjective for investors to determine the fundamental value of assets. This argument is related to a psychological framework within financial markets, which postulates that investment decisions are driven to a certain extent by psychological factors and emotions. As a result, changes in market prices are not necessarily supported by the fundamental value of assets Peterson (2016), and thus, market participants can profit by observing the differentials between the fundamental and psychological frameworks in pricing assets to identify under or overvalued assets.

Given the ambiguous nature of the crypto market and the lack of identifiable fundamental factors to which trends and price changes can be attributed, researchers have investigated whether and to what extent sentiment impacts the price dynamics of cryptocurrencies. This motivation is fuelled by evidence from studies where searches on Google and Wikipedia have been shown to significantly cause Bitcoin price movements at the aggregate level (Kristoufek 2013, Nasir et al. 2019). Furthermore, academics have shifted towards text-based sentiment analysis on social media platforms, including *Twitter* (Guégan & Renault 2020) and *Reddit* (Nasekin & Chen 2020), where they have documented proof of potential effects on the price discovery process in the crypto market. While these opinions and online searches may not seem to be contributing any additional information at face value, the collective nature of these opinions has been found to be a major driving force of cryptocurrency price dynamics.

4.2.1 Sentiment Analysis in Traditional Markets

Equity-centric blogs, such as StockTwits or even subreddits on the Reddit platform, have been shown to provide significant insight into the prediction of stock movements (Antweiler & Frank 2004, Nguyen et al. 2015, Li et al. 2018) — especially as was manifested in GameStop. Chen et al. (2014) use the dictionary of Loughran & McDonald (2011) to articles published on *SeekingAlpha* — an equity-centric platform — and show that the proportion of negative terms used negatively predicts stock returns over the subsequent three months. Similarly, Garcia (2013) applied the same dictionary to financial articles in the *New York Times* while controlling for popular trading strategies, and found that a one standard deviation shock to the level of pessimism inferred from the articles shifted the Dow Jones Industrial Average by 12 basis points during bear markets. Baker & Wurgler (2007) state that surveys including the American Association of Individual Investors (AAII) or Investor Intelligence (II) are very popular but are limited by their need for recipients to generate a representative sample. Moreover, several sentiment indicators have been used, including the CBOE Volatility Index (VIX) as well as cross-overs between moving averages of different rolling windows.

Nonetheless, the most prevalent framework that has been applied in the literature on sentiment analysis encompasses Twitter-based methodologies. Tweets on Twitter have been widely used as a source of data to gauge the sentiment of the market as they offer a combination of both, news as well as investor opinion and reaction to the news. The motivation for this is that micro-blogs and social media platforms facilitate the spread of generated content much faster than traditional news outlets, thus having a more immediate impact on financial markets. Studies such as Tafti et al. (2016), Peterson (2016), and Li et al. (2018) show that social media platforms and micro-blogs such as Twitter offer a reasonable live-stream of market information. Twitter data offers a rich source of information that has the potential to impact markets, which can be used to infer emotional intelligence through sentiment analysis. As such, researchers have used such data in order to assign a sentiment polarity score (positive, negative or neutral) to unstructured text (Liu & Zhang 2012). The sentiment score assigned to a text is a weighted product of the frequency with which words from each polarity category appear (Kearney & Liu 2014). Giachanou & Crestani (2016) differentiate among four types of methodologies used in the context of Twitter sentiment analysis, which include 1) supervised machine, 2) lexicon-based, 3) hybrid between machine learning and lexicon-based, and 4) a graph-based approach.

In an early and pioneering study, Bollen et al. (2011) use sentiment analysis on Twitter to forecast daily prices movements in financial markets. The authors use two mood tracking tools: the first called OpinionFinder measures the *positive* versus *negative* sentiment, while the second, called Google-Profile of Mood States, projects mood on six dimensions including *Calm*, *Alert*, *Sure*, *Vital*, *Kind*, and *Happy*. A Granger causality test and a Self-Organising Fuzzy Neural Network show that the mood time series is able to predict changes in the Dow Jones Industrial Index with an accuracy of over 87%. While this study has been criticised for making false statistical assumptions and inferences, others have aimed to address these concerns, including Li et al. (2018) who adopted a Naive Bayes sentiment classifier in combination with regression models and found evidence supporting the predictive power of stock-related tweets in relation to daily stock returns. Moreover, the findings show that the volatility in the previous day results in an increase in Twitter posts, implying that Twitter sentiment acts as both a "cause" and "effect" of asset price movements. Several other papers that adopt a methodological combination of Granger causality and regression models have also presented evidence that supports the predictive power of sentiment on Twitter in traditional financial markets (Zhang et al. 2011, Mao et al. 2011, Sprenger et al. 2014), with some (Bollen et al. 2011, Porshnev et al. 2013) applying Neural Networks as an auxiliary approach to examine the predictive power of Twitter sentiment.

Academics have highlighted several limitations of the Granger causality test with respect to bias and assumptions. One key limitation of the original Granger causality test is that it assumes the data is stationary and that relationships between the variables are linear. Many studies in the literature apply Granger causality to find predictor variables for asset returns; however, only a few studies underscore the fact that the relationships between variables are almost always non-linear, especially since there are several other factors that influence prices (Bollen et al. 2011, Balcilar et al. 2017).

Another limitation of hybrid methods that use a combination of machine learning models and a lexicon-based framework to measure sentiment is that they are highly dependent on the lexicon used to train the sentiment scoring model.

These studies often use the Loughran & McDonald financial corpus or the Harvard IV-4 psychological corpus (Mao et al. 2011, Li et al. 2014). In a popular study, Loughran & McDonald (2011) show significant improvements in the performance of a sentiment analysis classifier when a context-specific dictionary is used. As such, the predictive power of sentiment models is driven to a large extent by the lexicon or dictionary used to train the model.

Nevertheless, the significant work that has been done on sentiment in traditional markets has laid the foundations for researchers to apply similar methods in the cryptocurrency space. In the following section, I review some of these studies that aim to investigate the impact of sentiment on crypto price movements.

4.2.2 Sentiment Analysis in the Crypto Market

The application of text-based sentiment methodologies in the crypto space is relatively limited compared to more traditional financial markets. To some degree, this is due to cryptocurrencies being a novel asset class, with the first cryptocurrency, Bitcoin, being established in 2009. Since then, over 1,400 cryptocurrencies have been issued (Lee 2019); however, this market is still in its infancy, both in terms of size and available information, when compared to equity, debt, and commodity markets (Phillip et al. 2018).

Social media platforms and micro-blogs have become primary sources of information on cryptocurrencies. Studies including Mai et al. (2015), Kim et al. (2016), and Kim et al. (2017) have applied models to derive sentiment from messages on platforms such as *Reddit* and *Bitcointalk.org* in order to predict the price fluctuations of Bitcoin. In general, the findings offer evidence of the predictive power of social media and sentiment in predicting crypto returns over both, the short term (between 1 and 7 days), as well as longer horizons (between one and three months). Chen et al. (2019) build a crypto-specific dictionary of positive and negative words using posts on the social media platform *StockTwits*, which is applied by Liu & Tsyvinski (2021) to *Google* searches. The authors show that sentiment has significant positive power in predicting cryptocurrency returns. Georgoula et al. (2015) applied a Support Vector Machine (SVM) model and finds that sentiment can be used to predict Bitcoin's short-term price fluctuations with an accuracy of 89.6%. Another study by Garcia & Schweitzer (2015) uses a lexicon-based methodology with a Vector Autoregressive (VAR) model and a Granger causality test, and finds that heightened polarity in sentiment on Twitter often precede significant price fluctuations in Bitcoin. Mai et al. (2015) use intra-day data and report evidence of the predictive power of Twitter sentiment at the hourly frequency. Naeem, Mbarki, Suleman, Vo & Shahzad (2021) found that the Twitter Happiness Sentiment index of six major cryptocurrencies has statistically significant predictive power, whereby high and low sentiment can predict future cryptoasset returns. Moreover, Kraaijeveld & De Smedt (2020) used a cryptocurrency-specific lexicon-based sentiment analysis methodology, paired with a Granger causality test, and found that Twitter sentiment can predict the returns of Bitcoin, Litecoin and Bitcoin Cash. When applying a ratio that measures market bullishness, the authors find predictive power for EOS and TRON (two other major cryptocurrencies). More recent studies have applied deep learning methods to create sentiment measures. For instance, Nasekin & Chen (2020) used recurrent neural networks

(RNNs) to develop sentiment indices based on user messages on *StockTwits* and reported a significant effect between sentiment and future crypto log-returns[2].

Other studies have focused on the relation between sentiment and market volatility. For example, Chen & Hafner (2019) infer sentiment from contributions to the social media platform *StockTwits* and show that volatility in crypto prices increases as sentiment decreases.

Another intriguing finding in the literature is that the number of postings and messages is positively correlated with Bitcoin's trading volume (Mai et al. 2015), suggesting a form of cyclical effect whereby extreme sentiment causes traders to trade similarly and move the market, which in turn produces greater extreme sentiment further propagating this cycle. This effect may compound as Karalevicius et al. (2018) shows that crypto investors tend to overreact to news resulting in an anomaly where initially the price moves in the same direction as the sentiment and then follows a slight correction.

4.2.3 Limitations of Sentiment Measures based on Social Media

The studies in the literature that adopt social media information to gauge trader sentiment in the crypto market are subject to several limitations. First, the sentiment models used are limited by a small subset of pre-selected search terms and

[2]The adoption of deep learning models in finance is relatively new and slow as there is a growing debate as to whether more complex models improve the accuracy of sentiment classifiers of textual information (Renault 2020).

queries that do not cover all languages use on the social media platforms. This biases the sample of messages, and consequently the sentiment score, towards the languages and words used in the search. Second, researchers apply extensive pre-processing methods such as tokenisation, stemming, punctuation-removal, among other filtrations, to clean the data used for the sentiment model. This may eliminate potentially important information, which may completely alter the meaning and sentiment of certain posts. Third, studies that use a lexicon-based approach often use the Loughran & McDonald financial corpus (Mai et al. 2015, Karalevicius et al. 2018), which may be outdated relative to the speed of innovation and jargon used in the crypto space. As such, the sentiment classification model used may not be capturing a significant proportion of the information contained in blog posts and messages that could explain much of the variation in crypto prices. Fourth, the search API of Twitter for instance, limits the user to a maximum of 180 queries every 15 minutes. This means that the studies that use Twitter information to construct their sentiment score are only using a small fraction of the full scope of Tweets available on the platform, therefore rendering the results not generalisable. Fifth, the 280-character limit of Tweets renders such data highly noisy and suitable to sentence-level analyses, which can be very general and could be misinterpreted (Giachanou & Crestani 2016). Finally, it is widely known that a large number of accounts on social media platforms, including Twitter, are robots or bot accounts. There are typically used to spread false information, or scam other participants by promising free giveaways and rewards for completing acts such as liking a post or retweeting it[3]. Similarly, Wright & Anise (2018) show ev-

[3]See `https://www.coindesk.com/markets/2018/05/30/6-outrageous-moments-in-crypto-twitter-scam-history/`

idence of a Twitter cryptocurrency bot network of over 15,000 accounts, which underscores the importance of distinguishing between the sentiment coming from information of real accounts and those that are simply regurgitated by bots to push forward a certain agenda or fake news.

The above-mentioned limitations have motivated me to use an alternative measure of sentiment in the cryptocurrency market, which is derived from blockchain data. Specifically, I use a combination of on-chain and off-chain transaction data to derive a measure of sentiment. I highlight that on-chain data has more recently developed along with innovations in decentralised finance (DeFi) to include data generated from alternative applications, including protocols for loanable funds, non-fungible tokens (NFT) market places, among other implementations. However, for the purpose of this study and given the period under analysis, I focus on blockchain transactions representing movements of assets between wallets.

4.3 Methodology

4.3.1 A sentiment score based on on-chain data

Based on the notion that the primary purpose of cryptocurrencies is a censorship-resistant *store of value*, it is crucial to understand the state of the crypto network in relation to the price at which the market is valuing the network. A key question that investors are keen to know the answer to is: at any given moment in time, how much of a cryptocurrency's circulating supply is in a state of profit or loss?

To answer this question, the use of on-chain data is of paramount importance to help investors gain insights into the fundamental value of cryptocurrencies. Before delving into the methodology, I introduce terminologies and concepts that are the building blocks of the sentiment measure used in this paper.

- **Unspent Transaction Output (UTXO):** An unspent transaction output, or UTXO, represents the amount of a digital currency that has been authorised to be used in a transaction. This essentially defines where each transaction on the blockchain begins and ends, and is a fundamental characteristic of the Bitcoin network as well as several other large blockchains. When a crypto transaction is initiated, one (or several) UTXOs serve as inputs, where a user will then digitally sign to confirm their ownership over the inputs. The part of the UTXO that is consumed is then considered as "spent" and no longer owner by the user who initiated the transaction. Subsequently, the unused outputs from the transactions become new UTXOs that can be spent in other transactions. To illustrate, consider an investor, Investor A who has 0.5 BTC in their wallet. This amount should not be thought of as a fraction of a Bitcoin, but rather a collection of UTXOs. Investor A then decides to send Investor B an amount equal to 0.4 BTC, which means that 0.4 BTC will be sent from Investor A to B (the first UTXO), and 0.1 BTC will be sent from Investor A back to their own wallet (the second UTXO). Thus, the transaction initiated by Investor A resulted in two new UTXOs, which is the mechanism used to keep track of where digital assets are at any moment in time and at what price there transactions were realised.

- **Market Value of Circulating Supply:** The market value of circulating supply of a digital asset, or better known as the market capitalisation, is the product of the current price and the total number of coins in circulation. This gives an indication of the dollar value the market is placing on the entire network, given the last transacted price on an exchange.

- **On-chain Cost Basis:** The on-chain cost basis of a digital asset on the other hand multiplies the circulating supply by the price at the time a UTXO occurred (i.e. the price at the time a coin moved on the network and its value was recorded on-chain). In contrast to the market capitalisation, the on-chain cost basis adjusts for two factors: 1) lost coins, and 2) coins that are being held (or "hodled" to use crypto slang). Both of these factors allow investors to estimate the number of coins that are "locked" and have not been a contributing part of the circulating supply. Therefore, the on-chain cost basis establishes an estimate of investors' cumulative cost basis, or in other words, a reference point of value for the network.

In order to estimate what portion of the circulating supply of a digital asset is in a profit (loss), we need to count all existing UTXOs whose price at transaction time on the blockchain was lower (higher) than the current market price on exchanges. In other words, we weight each circulating coin by the difference between the current price and its on-chain cost basis and sum up all the coins in profit and loss separately in order to calculate the unrealised profit and loss, respectively. Mathematically, for all $UTXOs = [1, \ldots, I]$ on a blockchain, the Unrealised Profit (UP) and Unrealised Loss(UL) can be expressed as:

$$UP = \sum_{UTXO_i=1}^{I} Q_i \times max(0, P_{current} - C_{UTXO,i}) \tag{4.1}$$

and

$$UL = \sum_{UTXO_i=1}^{I} Q_i \times max(0, C_{UTXO,i} - P_{current}) \tag{4.2}$$

where Q_i represents the nominal quantity of the digital asset being considered (ex:. units of Bitcoin), $P_{current}$ is the current value of the digital asset as traded on an exchange, and $C_{UTXO,i}$ is the cost basis or price of the digital asset at the time it was last moved on the blockchain.

While the UP and UL metrics tell us the dollar value of the gains and losses, respectively, of coins since they were last moved on the blockchain, standardising these estimates by the market capitalisation produces more informative measures of the proportion of the network that is in a relative gain or loss. Mathematically, the Relative Unrealised Profit (RUP), and the Relative Unrealised Loss (RUL) can be expressed as

$$RUP = \frac{UP}{MV} \tag{4.3}$$

and

$$RUL = \frac{UL}{MV}. \tag{4.4}$$

A growing consensus, as illustrated by several online articles[4], is that as the RUP tends towards one, this suggest that the market has reached a top thus triggering a sell-off. Conversely, a higher value for RUL implies the market has reached a bottom and thus a signal to buy the asset as it is deemed undervalued.

By taking the difference between RUL and RUP, we calculate the Net Unrealised Profit/Loss ($NUPL$) as:

$$NUPL = RUP - RUL. \tag{4.5}$$

The $NUPL$ tells investors whether the entire blockchain of a particular digital asset is in an overall state of relative gain or loss. While this metric represents a

[4] See `https://medium.com/glassnode-insights/dissecting-bitcoins-unrealised-on-chain-profit-loss-73e735020c8d`.

continuous range of relative gain and loss differentials, several thresholds — while somewhat arbitrary — have been adopted and attributed to different sentiment categorisations throughout the macro cycles of a digital currency[5,6]. Specifically, market sentiment, labelled as *Sentiment*, is mapped to the value or state of a digital blockchain according to the following value ranges of $NUPL$:

- Very High: $NUPL > 0.75$
- High: $0.5 < NUPL \leq 0.75$
- Neutral: $0.25 < NUPL \leq 0.5$
- Low: $0 < NUPL \leq 0.25$, and
- Very Low: $NUPL \leq 0$.

The frequency of these regimes of $NUPL$ are:

- Very High: 13.28%
- High: 15.44%
- Neutral: 40.30%
- Low: 29.51%, and
- Very Low: 1.48%.

[5] See `https://medium.com/glassnode-insights/dissecting-bitcoins-unrealised-on-chain-profit-loss-73e735020c8d`.

[6] See `https://medium.com/@kenoshaking/bitcoin-market-value-to-realized-value-mvrv-ratio-3ebc914dbaee`

Figure 4.1 plots the log-price of BTC/USD and $NUPL$ on separate axes. For a better illustration of the relationship between market sentiment and Bitcoin price dynamics, I superimpose the sentiment score as a colour on top of the price of Bitcoin. This is shown in Figure 4.2.

Figures 4.3 and 4.4 show additional versions that plot data for the sample period.

I use both, the continuous values of $NUPL$ as well as the above-mentioned ordinal categories in a series of regression models in order to estimate the impact of market sentiment on trader performance as well as trading activity.

One important thing to note is that, while $NUPL$ increases as market price increases, it does not specifically capture (short-term) momentum in prices, as it is calculated over relatively long time horizons. For instance, a cryptocurrency may be transferred on-chain at a certain price level for a while, and subsequently, move to a higher price level. The cost basis, in this case, will increase but will be biased toward the lower price. On the other hand, the market value of the cryptocurrency will also increase but will be estimated at the new higher price level. Thus while both the cost basis and market value have increased, $NUPL$ is more of a historical cost accounting metric as it calculates the contemporary value of the crypto coin relative to its historical average traded value on-chain. Alternatively, a momentum indicator would mainly be focused on short-term price changes rather than the overall state of unrealised profit or loss of an asset.

I have conducted analysis to show the relationship between NUPL and momentum. Figures 4.5 and 4.6 show the price of Bitcoin, as well as the Bitcoin NUPL, daily, 90-day and 250-day returns. Even though Bitcoin price, NUPL and rolling returns tend to often follow the similar pattern on the chart, we can see that price momentum and NUPL are different things.

Moreover, I have also produced the correlation analysis between NUPL and price momentum.

As it can be seen in the correlation matrix in the Table 4.6, the change in NUPL, given by NUPL-pct-chng-day, is ceteris paribus not correlated with the percentage changes in Bitcoin prices. The correlation between the change in NUPL on a daily basis with Bitcoin returns on the same frequency is only -0.11%; the same correlation on a weekly basis is -0.04%. Overall, the correlations between daily Bitcoin returns and daily, weekly, monthly, 60, 90, 180 and 250-days NUPL return are close to zero; the same correlation is on a weekly Bitcoin basis too.

There are varying degrees of correlation between Bitcoin returns themselves, ranging from 6.82% for Bitcoin daily and 180-days returns to 88.27% between 180 and 250 days returns. This means that long-term Bitcoin returns tend to move together and in the same direction. Overall, although the Bitcoin returns, especially long-term Bitcoin returns, are relatively strongly positively correlated with each other, NUPL returns and Bitcoin returns are uncorrelated. This means that NUPL and momentum measure different things.

4.3.2 Calculating trader performance

Similar to Section 2.3 in Chapter 2, I decompose total profit or PnL into realised and unrealised components in order to assess the impact of market sentiment on the active component of trader performance. Specifically, the realised PnL represents the impact of active portfolio management that captures the increase or decrease of quantities of assets in terms of units, while the unrealised PnL represents the outcome of the passive holding of a portfolio relative to a reference base asset.

To calculate the above-mentioned total profit as well as the components let $m = 1, \ldots, M$ denote the unique identifier of each asset in the investable universe, $n = 1, \ldots, N$ represent the unique trader identifier, and t represent the timestamp at which a valuation assessment of all balances is made. At each profit calculation, I define the units of each asset for each trader as $Q^t_{m,n}$, the net deposits in units as $ND^t_{m,n}$, and the prices of each asset against USD as P^t_m. At any time t the value of a trader's balance for a given asset m is calculated as $P^t_m \times Q^t_{m,n}$. Furthermore, this can be calculated by taking the balance at the previous period, $P^{t-1}_m \times Q^{t-1}_{m,n}$, adjusting the value due to price changes over the assessment period, $(P^t_m - P^{t-1}_m) \times Q^{t-1}_{m,n}$, adjusting the balance for any changes in the number of units due to active trading $(Q^t_{m,n} - Q^{t-1}_{m,n}) \times P^t_m$, and accounting for net deposits valued at the price at time t, $ND^{t-1}_{m,n} \times P^t_m$.

This equation can be expressed across multiple assets as

$$\begin{aligned} P^t_m \times Q^t_{m,n} = & P^{t-1}_m \times Q^{t-1}_{m,n} + (P^t_m - P^{t-1}_m) \times Q^{t-1}_{m,n} \\ & + (Q^t_{m,n} - Q^{t-1}_{m,n}) \times P^t_m + ND^{t-1}_{m,n} \times P^t_m \end{aligned} \tag{4.6}$$

To calculate total profit, which is the overall change in value between two consecutive balances adjusted for net deposits, I rearrange the above equation as

$$\begin{aligned} P_m^t \times Q_{m,n}^t - P_m^{t-1} \times Q_{m,n}^{t-1} - ND_{m,n}^{t-1} \times P_m^t = \\ (P_m^t - P_m^{t-1}) \times Q_m^{t-1} + (Q_{m,n}^t - Q_{m,n}^{t-1}) \times P_m^t \end{aligned} \tag{4.7}$$

As such, total profit can be calculated as

$$Total\, PnL_{m,n}^t = (P_m^t - P_m^{t-1}) \times Q_{m,n}^{t-1} + (Q_{m,n}^t - Q_{m,n}^{t-1}) \times P_m^t \tag{4.8}$$

The component $(P_m^t - P_m^{t-1}) \times Q_{m,n}^{t-1}$ captures the unrealised profit, which represents the change in value due to the passive holding of an asset, while the term $(Q_{m,n}^t - Q_{m,n}^{t-1}) \times P_m^t$ represents the realised profit due to active trading resulting in changes in the number of units of an asset not related to deposit or withdrawal activities.

Using Δ to represent differencing, I write the two trading components as

$$Unrealised\, PnL_{m,n}^t = \Delta P_m^t \times Q_{m,n}^{t-1} \quad \text{and} \quad Realised\, PnL_{m,n}^t = \Delta Q_{m,n}^t \times P_m^t. \tag{4.9}$$

To convert dollar profits into returns I divide the respective profit measures by the starting balance value of each assessment period — weekly in this paper.

4.3.3 Regression models

Studies on sentiment in financial markets have mainly focused on examining the impact of text-based sentiment metrics on asset returns.

For instance, Chen et al. (2014) utilise the Loughran & McDonald (2011) dictionary to articles published on *SeekingAlpha*, use the cross-sectional regression and report that the proportion of negative words used negatively impacts stock returns over the subsequent three months. Garcia (2013) adopts the same dictionary to articles published in the *New York Times*, and find that a one standard deviation shock to the degree of media pessimism shifts the Dow Jones Industrial Average by 12 basis points during recessions. Sprenger et al. (2014) apply a classifier to stock-related texts on *Twitter*, use contemporaneous regressions with tweet features as independent variables and the market return as a control, returns, abnormal returns, trading volume and volatility as dependend variables, use Fama-MacBeth cross-sectional regressions, and find significant contemporary relationships between tweet bullishness and abnormal returns. The authors also document a positive effect between the degree of online disagreement and trade volatility, which is based on the earlier work of Antweiler & Frank (2004) who run contemporaneous regressions and show that disagreement is linked to an increase in trading activity, when trading activity, regressed on disagreement, has a positive sign. The evidence presented by these studies are consistent with prior models (Harris & Raviv 1993) which predict that investors receive common information that is interpreted differently, resulting in uncertainty and higher trading volumes.

In the crypto space, Corbet et al. (2020) apply a similar dictionary methodology and show that cryptocurrency returns are significantly impacted by the degree of negative *Twitter* sentiment arising due to the COVID-19 pandemic. Chen et al. (2019) assemble a crypto-specific dictionary of positive and negative words based on messages posted on *StockTwits*, and find that sentiment positively and significantly predicts cryptocurrency returns. Another study by Guégan & Renault (2020) shows significant relationships between sentiment and Bitcoin returns for intra-day frequencies of up to fifteen minutes. Abraham et al. (2018) use tweet volumes and *Google Trends* index levels as proxies for public interest, and find high levels of association with cryptocurrency prices, while a more recent study by Valencia et al. (2019) constructs sentiment indices using *Twitter* content and shows a price prediction accuracy over 50% for cryptocurrencies including Bitcoin, Ethereum, Ripple and Litecoin.

The above-mentioned literature has motivated me to investigate sentiment in crypto markets from another dimension, by examining its impact on trader performance and trade exposure.

Using the sentiment and performance metrics presented in the sections above, as well as other trading activity and demographics control variables, I run several regression models in order to assess the impact of market sentiment of trader performance and trading activity.

The first set of models use two lagged one-period changes in the Bitcoin $NUPL$ values, given by $\Delta NUPL_{BTC,t,t-1}$ and $\Delta NUPL_{BTC,t-1,t-2}$, respectively, to examine the impact of market sentiment on trader performance and trade size. Specifically, Model (3.1.a) uses the $TotalROI$ as the dependent variable to estimate the impact of sentiment on overall performance, Model (3.2.a) uses the $RealisedROI$ to isolate performance due to active trading, Model (3.3.a) uses the natural logarithm of the dollar value of the trade executed by the trader (denoted as $log(Volume)$), and Model (3.4.a) uses the percentage change in the log-volume, given by $\Delta log(Volume)$, to estimate the impact of market sentiment on changes in future trader exposures.

For all the above-mentioned models, I include as controls two-period lagged values of the $RealisedROI$, and two-period lagged values of the log-volume, $log(Volume)$. Moreover, I include control variables for each trader that are calculated up to but not including time t, such as the natural logarithm of the average trade size, $log(AverageTrade)$, the natural logarithm of the average balance size, $log(AverageBalance)$, the cumulative number of trades executed, $NumberTrades$, the number of unique markets traded, $NumberMarkets$, and the volatility of the cryptocurrency market, $Volatility$, proxied by the standard deviation of hourly price returns of the Bitcoin-Dollar market. Additionally, I control for demographics such as geographical location (proxied by the $Continent$ on which the trader is located, where $Continent$ = [Africa, Americas, Asia, Europe, Oceania]) as well as age, given by the five age groups (18, 30], (30,40], (40,50], (50,60], and (60, 60+]. All models are augmented with trader fixed effects (α).

Mathematically, I express the above-mentioned models as:

$$\begin{aligned} TotalROI_{n,t} = {} & \omega_1 \Delta NUPL_{BTC,t,t-1} \\ & + \omega_2 \Delta NUPL_{BTC,t-1,t-2} + Controls + \varepsilon_{n,t} \end{aligned} \tag{3.1.a}$$

$$\begin{aligned} RealisedROI_{n,t} &= \omega_1 \Delta NUPL_{BTC,t,t-1} \\ &\quad + \omega_2 \Delta NUPL_{BTC,t-1,t-2} + Controls + \varepsilon_{n,t} \end{aligned} \tag{3.2.a}$$

$$\begin{aligned} log(Volume)_{n,t} &= \omega_1 \Delta NUPL_{BTC,t,t-1} \\ &\quad + \omega_2 \Delta NUPL_{BTC,t-1,t-2} + Controls + \varepsilon_{n,t} \end{aligned} \tag{3.3.a}$$

$$\begin{aligned} \Delta(log(Volume)_{n,t}) &= \omega_1 \Delta NUPL_{BTC,t,t-1} \\ &\quad + \omega_2 \Delta NUPL_{BTC,t-1,t-2} + Controls + \varepsilon_{n,t} \end{aligned} \tag{3.4.a}$$

where

$$\begin{aligned} Controls = &\sum_{q=1}^{2} \kappa_q RealisedROI_{n,t-q} + \sum_{q=1}^{2} \gamma_q log(Volume)_{n,t-q} \\ &+ \delta_1 log(AverageTrade)_{n,t} + \delta_2 log(AverageBalance)_{n,t} \\ &+ \delta_3 NumberTrades_{n,t} + \delta_4 NumberMarkets_{n,t} \\ &+ \sum_{q=0}^{2} \sigma_q Volatility_{t-q} + \sum_{l=(30,40]}^{L} \lambda_l Age_{n,l} \\ &+ \sum_{c=Asia}^{C} \kappa_c Continent_{n,c} + \alpha_n \end{aligned}$$

As an alternative to the continuous $NUPL$ parameter, I run another set of models using the categorical *Sentiment* variable to check whether and to what extent the predefined levels of sentiment impact trader performance and trade size. Using the same controls as above, I define four models as follows:

$$TotalROI_{n,t} = \sum_{q=0}^{1} \beta_{L,t-q}Low_{t-q} + \beta_{N,t-q}Neutral_{t-q} + \beta_{H,t-q}High_{t-q} + \beta_{VH,t-q}VeryHigh_{t-q} + Controls + \varepsilon_{n,t} \tag{3.1.b}$$

$$RealisedROI_{n,t} = \sum_{q=0}^{1} \beta_{L,t-q}Low_{t-q} + \beta_{N,t-q}Neutral_{t-q} + \beta_{H,t-q}High_{t-q} + \beta_{VH,t-q}VeryHigh_{t-q} + Controls + \varepsilon_{n,t} \tag{3.2.b}$$

$$log(Volume)_{n,t} = \sum_{q=0}^{1} \beta_{L,t-q}Low_{t-q} + \beta_{N,t-q}Neutral_{t-q} + \beta_{H,t-q}High_{t-q} + \beta_{VH,t-q}VeryHigh_{t-q} + Controls + \varepsilon_{n,t} \tag{3.3.b}$$

$$\Delta(log(Volume)_{n,t}) = \sum_{q=0}^{1} \beta_{L,t-q}Low_{t-q} + \beta_{N,t-q}Neutral_{t-q} + \beta_{H,t-q}High_{t-q} + \beta_{VH,t-q}VeryHigh_{t-q} + Controls + \varepsilon_{n,t} \tag{3.4.b}$$

Note that I use the "Very Low" market sentiment category as the base category in the above-mentioned regression models.

4.4 Data

4.4.1 Market and Network Data

The calculation of the net unrealised profit loss, $NUPL$ is based on on-chain network data that is obtained from Glassnode[7]. As mentioned above, $NUPL$ is calculated as the difference between the market cap and on-chain cost basis of a cryptocurrency, and dividing the result by the market cap. Data on UTXOs is only available for Bitcoin and Ethereum, the two largest cryptocurrencies by market cap, with a granularity of one hour sampling frequency.

Over the period 2012 to 2021, the $NUPL$ time-series for Bitcoin and Ethereum have a high correlation of 78.53%. As such, for the purpose of this research, I calculate and use only the $NUPL$ for Bitcoin to circumvent the issue of multicollinearity in my regression models. Moreover, most cryptocurrencies traded by individuals in the data set used in this study were highly correlated with Bitcoin over the period of analysis. As such, I use Bitcoin as a proxy for the cryptocurrency market.

As mentioned earlier, Figure 4.1 and Figure 4.2 illustrate the relation between Bitcoin price and $NUPL$ for the Bitcoin network.

[7] See `https://glassnode.com`.

4.4.2 Exchange Data

The trader data used this paper comes from an anonymous crypto exchange called ExchangeX, where trading is conducted in spot markets. Traders can execute both market and limit orders which enter the order book and are then matched by a matching engine. The data set covers over 1.5 million trades for the period from June 2017 to December 2018. I present descriptive statistics in Panel A of Table 4.1.

Examining account age reveals a median of 27 days, indicating more than half of the accounts operate for less than a month. Some accounts exist for just a day, which could arise from trial users or others dissatisfied with the platform's offerings. The average account age is 101 days, suggesting the coexistence of many short-lived accounts with longer-term ones.

The age range of traders is 20-71 years, with a majority in their mid-thirties. Younger traders, primarily in their late twenties and early thirties might be tech-savvy, while those above 40 might prioritise financial security.

In asset selection, many traders focus on 2-3 crypto assets, potentially due to familiarity or the perceived reduced risk with popular assets. Yet, some engage with up to 65 different assets, hinting at a strategic diversification approach.

Considering trade frequency, the median of 19 trades points to a more conservative approach by over half the traders, but a small fraction record up to 50,871 trades, likely stemming from algorithmic trading or institutional participation.

Trade volume varies widely, ranging from \$1 to \$620,021. While the average trade size is \$489, the more representative median stands at \$201, indicating the presence of outlier trades from affluent traders or institutions.

Using the formulations presented in 2.3, I first calculate the weekly total dollar profits and losses (PnL) as well as the decomposed realised and unrealised components. To make these figures comparable across transactions and traders, I standardise the profits to calculate percentage returns by dividing the total, realised, and unrealised profits by the starting balance of each period to obtain $TotalROI$, $RealisedROI$, and $UnrealisedROI$, respectively. The aggregated results are presented in Panel B of Table 4.1.

4.5 Results

4.5.1 Sentiment and Trader Performance

4.5.1.1 Total ROI and Sentiment

In the first analysis, I investigate whether and to what extent market sentiment (as proxied by $NUPL$) impacts the total return of traders. The results for Model (3.1.a) and Model (3.1.b) are presented in Table 4.2. For Model (3.1.a), I find positive coefficients of 0.003 for the $\Delta NUPL_{BTC,t,t-1}$ and $\Delta NUPL_{BTC,t-1,t-2}$ parameters, suggesting that a positive change or increase in the total network unrealised profit in the previous periods, leads to higher $TotalROI$ levels in the future. This may be due to a momentum effect in market prices that is driven by on-chain activity. In other words, when there is a positive change in sentiment on the network, this results in an increase in total returns for traders. In order to better understand the effects of the different levels of sentiment on $TotalROI$, I run Model (3.1.b), which uses the categorical $Sentiment$ variable. Using the category "Very Low" as the base reference level, the results show that as market sentiment moves from "Low" to "Very High", the effect on $TotalROI$ increases substantially. This finding is also true for the lagged $Sentiment$ variable. These results suggest that traders experience the highest levels of total returns when the market is in a state of very high sentiment.

Regarding the lagged $RealisedROI$ covariates, I report positive coefficients of around 0.8 for the lagged $RealisedROI_{t-1}$ variable, suggesting that past realised returns are significantly and positively correlated with future total returns. This may be due to the consequential effects of traders' past decisions on the future total performance of their portfolios. Nevertheless, I also report a negative, yet much smaller effect of the two-period lagged $RealisedROI_{t-2}$ variable. This implies that there is a minor reversion in the relation between the returns of past trading decisions and future total performance. As for the remaining covariates, I find similar results across both Model (3.1.a) and Model (3.1.b). Specifically, I find negative coefficients for the lagged $log(Volume)$ parameters across both models with values around -0.001, which suggests that there is a negative yet small relation between past trade size and future total performance. This may be due to the possible negative price impact that larger trades have on portfolio performance. However, when looking at the $log(AverageTrade)$ variable, I report positive coefficients between 0.007 and 0.009, suggesting that traders with relatively larger career trade sizes tend to experience higher total future returns. Similarly, I find that traders with larger balances tend to experience marginally higher total returns. This may be due to these traders having greater exposure to crypto assets, which have witnessed significant growth over the period of study. I report a negative coefficient of -0.001 for the $NumberTrades$ variable, indicating that excessive trading is detrimental to total returns. This is in line with the literature on active trading among retail investors (Barber & Odean 2000). Regarding the number of markets traded, $NumberMarkets$, I find coefficients of 0.001 and 0.002 for Models (3.1.a) and (3.1.b), respectively, which indicates that diversification across markets generates a marginal advantage in terms of total future returns. With respect to lagged market volatility, I find small negative coefficients of -0.0001 for both $Volatility_{t-1}$ and $Volatility_{t-2}$. This means that higher volatility in the previous periods results in lower total returns, that may be driven by subsequent bearish market trends. I do not find any significant results for the *Age* and *Continent* parameters, which suggests that trader experience (as proxied by age) and geographical location do not have any effect on the total returns of a trader's portfolio.

4.5.1.2 Realised ROI and Sentiment

The above analysis uses total returns as the dependent variable; nevertheless, we may be more interested in understanding the effects of market sentiment on the active component of returns driven by trader decisions. To do so, I run Models (3.2.a) and (3.2.b) and present the results in Table 4.3. For Model (3.1.a) I find positive coefficients for the $\Delta NUPL$ parameters. These results imply that positive changes in the level of sentiment lead to higher realised returns. I also examine the impact of the categorical *Sentiment* variable on realised returns in Model (3.2.b) and find positive yet small coefficients for the contemporaneous *Sentiment* parameter which increase with the level of $NUPL$ in the network (i.e. as we move from very low to very high market sentiment), while I report negative coefficients for the lagged covariate. This means that traders who react immediately to market sentiment, specifically during times of very high market sentiment, are likely to realise higher positive returns. Nonetheless, traders also experience a negative effect on realised returns of the same magnitude as market sentiment begins to wane.

With respect to the lagged *RealisedROI* covariates, I report positive coefficients of around 0.825 for the lagged $RealisedROI_{t-1}$ variable, suggesting that past realised returns are significantly and positively correlated with future realised returns. At first glance, this finding contrasts what has been reported in the literature by Gemayel & Preda (2021), who show that, in general, realised returns follow a mean-reversion pattern. Nonetheless, the authors also show that there is positive auto-correlation in realised returns during bearish markets. Given that my data set predominantly covers the bearish period (i.e. after January 2018) of the crypto market, the results echo what is reported in the literature[8]. I also report a small negative coefficient for the $RealisedROI_{t-2}$ variable, which suggests that there is a minor reversion in the relation between past and future realised returns. I do not find any significant effect for the lagged $log(Volume)$ parameters, suggesting that the size of past trades has no impact on future realised performance. Nevertheless, traders with larger career trade and balance sizes tend to realise marginally higher returns, as indicated by the positive and significant coefficients of the $log(AverageTrade)$ and $log(AverageBalance)$ parameters. These results may be suggestive of trader sophistication where those with more wealth have access to superior trading and risk management tools, granting them an advantage in the highly volatile crypto market. The negative coefficients for the $NumberTrades$ variable suggests that excessive trading is detrimental to realised returns — as has been highlighted din the literature (Barber & Odean 2000). Regarding the number of markets traded, traders who diversify across multiple markets experience a marginal improvement in realised returns. Hence, diversification may improve returns, although this result is relatively minor. I find that volatility,

[8] In unreported results, I conduct a robustness check where I run Models (3.2.a) and (3.2.b) on the period post January 2018 and find similar results to the analysis on the full data set.

as captured by the lagged $Volatility$ parameters, is detrimental to performance. This suggests that traders execute sub-optimal trades when market uncertainty is high. The categorical *Age* parameters show that there is somewhat of a concave relation with realised returns, whereby traders aged between 40 and 50 years experience higher realised returns. This may be due to their relatively greater experience in trading — though not necessarily in the crypto space as this asset class is relatively novel to traders of all ages. Finally, I do not find any significant relation between the geographical location of a trader and realised returns. This suggests that trader performance is not impacted by the local regulations governing the jurisdiction in which they are located.

4.5.2 Sentiment and Trade Exposure

4.5.2.1 Trade Size and Sentiment

In the following analysis, I examine whether and to what extent market sentiment impacts the size of trades. I present the results of Models (3.3.a) and (3.3.b) in Table 4.4. I report a positive coefficient of 0.002 for the $\Delta NUPL_{BTC,t,t-1}$ parameter and no statistical significance for the $\Delta NUPL_{BTC,t-1,t-2}$ parameter. This means that a positive change in market sentiment results in larger trade sizes; hence, traders increase their exposure when market sentiment is relatively high. The categorical *Sentiment* variable in Model (3.3.b) shows that trade size grows substantially as market sentiment shifts towards very high levels. This is also true for the lagged *Sentiment* variable, although the coefficients are of a smaller magnitude. As mentioned earlier, a state of very high market sentiment implies generally higher levels of market prices, which translates into larger trade sizes. Hence, the effect of market sentiment on trade size may not be definitive in this analysis.

For the two Models (3.3.a) and (3.3.b), I report negative and statistically significant coefficients of around -0.2 for $RealisedROI_{t-1}$, and around -0.06 for $RealisedROI_{t-2}$. This means that traders who perform poorly in the past due to their active decisions are likely to increase their future trade size, which is indicative of the gambler's fallacy. Hence, those who experience poor past returns are likely to increase their trade size to try and make up for their sub-optimal trading decisions. Regarding the lagged $log(Volume)$ variables, I report negative coefficients of -0.711 for $log(Volume)_{t-1}$ and -0.045 for $log(Volume)_{t-2}$. This suggests that there is a negative auto-correlation between past and future trade sizes, and is in line with the notion that traders with poor past performance are likely to increase their future trade size to make up for their historically sub-optimal trading decisions. I do find positive coefficients for the career trade size and balance size, given by $log(AverageTrade)$ and $log(AverageBalance)$, respectively. These results are intuitive since those with larger balances and average trade sizes are likely to execute relatively larger future trades. I find that those who trade more and across multiple markets tend to have lower future trade sizes, which may be due to these traders spreading their balance across multiple trades and across a wider investable universe. Lagged market volatility has a weak and negative effect on future trade size, implying that traders subsequently reduce their exposure after having experienced volatile market periods. This can be seen as traders aiming to manage their exposures and risks through smaller trades. Regarding trader age, I report that those in the group between 30 and 40 years generally have larger trade sizes as shown by the positive coefficients of 0.055 for both Model (3.3.a) and (3.3.b). This age group may be relatively wealthier and more prone to taking risks compared to their younger counterparts (i.e. age group 18 to 30 years), which manifests in larger trade sizes. I do not find any statistically significant coefficients for age groups (40, 50] and (50, 60]. However, I find negative coefficients of -0.14 across the two models for age group (60+]. This suggests that mature individuals have less exposure to crypto, which may be due to their lower level of comfort with this novel asset class. Finally, regarding traders' geographical location, I find positive coefficients for all *Continent* variables — note that Africa is taken as the base category. Specifically, I find larger coefficients for traders located in Oceanian and Asian countries compared to those located in Africa, America, and Europe, which may be due to their greater degree of wealth and higher exposure to the crypto asset class.

4.5.2.2 Change in Trade Size and Sentiment

Since the size of a trade (given by the product of price and volume) is mathematically linked to $NUPL$ (which incorporates market prices into the equation) making it challenging to estimate the impact of market sentiment on future trade exposure, I run an alternative analysis where I use the change in trade size as the dependent variable. Hence, Models (3.4.a) and (3.4.b) allow us to investigate whether market sentiment drives traders to change the size of their trades. Regarding Model (3.4.a), I find no statistical significance for the $\Delta NUPL$ parameters, meaning that changes in the level of $NUPL$ do not impact traders to change their trade sizes. With respect to the categorical *Sentiment* variable, I do not find any significant relationships for either the contemporary or lagged sentiment factors. This echoes the results obtained for Model (3.4.a) whereby market sentiment has no significant effect on traders changing their trade sizes. These results suggest that a "change" in trade size is agnostic to market sentiment, and thus traders do not change their exposure according to market sentiment. I find negative and statistically significant coefficients of around -0.097 for $RealisedROI_{t-1}$, and around -0.063 for $RealisedROI_{t-2}$, which suggests that traders who perform poorly in the past due to their active decisions are likely to increase their future trade size to make up for sub-optimal past trading decisions. This is similar to the results of Models (3.3.a) and (3.3.b), which are indicative of the gambler's fallacy among crypto traders.

I do not find any significant coefficients for the lagged $log(Volume)$ variables nor for the $log(AverageTrade)$ variable, which implies that past trade size does not impact a trader's decision to change subsequent trade sizes. As such, the size of a trade is somewhat of a "sticky" input into the trading strategy. I find positive coefficients for the $log(AverageBalance)$ across the two models, which means that those with larger balances tend to increase the size of their future trades by a marginal amount. The results also show that those who trade more and across multiple markets tend to reduce their exposure on future trades, which may be due to these traders spreading their balance across multiple trades and across a wider investable universe. Lagged market volatility drives traders to reduce their exposure on future trades, which can be interpreted as a way for traders to manage their risk exposure. Regarding the age of traders, I find that those in the group between 30 and 40 years generally have larger trade sizes as shown by the positive coefficients of around 0.044 for both Model (3.4.a) and (3.4.b). Similar to the findings in the previous section, this age group may be relatively wealthier and more prone to taking risks compared to their younger counterparts. Moreover, I do not find any statistically significant coefficients for age groups (40, 50] and (50, 60], but I do report negative coefficients of -0.11 across the two models for age group (60+]. This implies that mature individuals are more likely to reduce their exposure to crypto, which may be due to their lower level of comfort with this asset class. Finally, I find positive coefficients for all *Continent* variables with larger coefficients for traders located in Oceanian, Asian, and European countries. This means that traders located in these regions are more likely to increase their exposure on future trades by larger proportions compared to traders located in other regions. As such, they can be seen to have a greater inherent risk-taking profile.

4.5.2.3 Alternative Sentiment Measures: The VIX

As a robustness check, I use the equity volatility index VIX instead of NUPL as an alternative measure of sentiment by categorising it into 5 volatility regimes. I rerun the above regressions and present the results in 4.7. In general, I find no consistent effect of the VIX on realised ROI, which implies that, while the VIX is often regarded as a common sentiment measure in the equity space, it does not explain trading returns in the cryptocurrency market. This underscores the importance of development of sentiment metric that is more tailored to the cryptocurrency space.

4.5.2.4 Relationship Between NUPL and Price Momentum

As another robustness test, I further examine the relationship between NUPL and price momentum by regressing NUPL on the 180 day returns of a market weighted index of the top ten cryptocurrencies. This allows me to obtain the residuals of the regression, which by default are not correlated with price momentum, but still explain the variation in NUPL. Next, I rank and categorise these residuals into 5 quantiles and include them in equation 3.2.b instead of NUPL. This allows me to filter out the momentum component that may be driving NUPL and test the impact of residuals on ROI, which capture the residual sentiment effect after accounting for momentum. I rerun the above regressions and present the results in 4.8. The results show that some, but not all, of the residual regimes have a negative relation to trading ROI, suggesting the residual regimes have no consistent relationship to ROI and therefore there is evidence that the effect of sentiment, via NUPL, is comparable to momentum.

4.6 Conclusion

This paper uses a unique data set of over 1.5 million transactions executed by over 15,000 traders on an anonymous crypto exchange and introduces a blockchain-based sentiment indicator (net unrealised profit loss or $NUPL$) as an alternative to the text-based models used in the literature to investigate the impact of market sentiment on trader performance and activity. The findings of this research are fourfold.

First, I find that changes in lagged values of $NUPL$ positively impact the total return experienced by traders. Moreover, traders experience the highest levels of total returns when market sentiment is very high.

Second, while positive changes in lagged values of $NUPL$ lead to higher realised returns, this effect though significant is relatively small. Moreover, traders who react immediately to market sentiment, specifically when the overall market sentiment is very high, are likely to realise higher positive returns.

Third, I find that positive changes in market sentiment lead to larger future trade sizes; hence, traders increase their exposure when market sentiment is high.

Finally, I find no relationship between changes in market sentiment and *changes* in trade size, suggesting that a "change" in trade size is agnostic to changes in market sentiment, and thus traders do not dynamically alter their exposure.

As a robustness check, I also adopted the VIX, a common equity market volatility index, to measure sentiment in the cryptocurrency market. The results showed that the VIX had no consistent impact on the realised ROI for cryptocurrency trading. This suggests that the VIX, while useful in the equity domain, is not a suitable indicator of sentiment for cryptocurrencies, pointing to the need for developing a sentiment measure specifically designed for the unique characteristics of the cryptocurrency market.

Note that while $NUPL$ serves as a proxy for the market's overall sentiment and aligns with long-term momentum, it is not the sole driver of individual trading decisions, particularly in the short term. The potential disconnect between NUPL and short-term price trends—where market sentiment may be low yet prices show temporary upward momentum—highlights the complexity of market dynamics. The findings are in line with other studies suggesting that market sentiment and price momentum may independently influence trader behaviour.

One of the implications of my findings is that people trade more aggressively, when the sentiment is high in the cryptocurrency markets, and that there is a lag between a NUPL variable and trading activity, so people tend to get more aggressive in high sentiment settings and less aggressive in low sentiment settings.

No research is without limitations, and in this study a limiting assumption that is made is that the market sentiment derived from the Bitcoin network is representative of the sentiment across all cryptocurrencies traded by traders on the anonymous exchange. While Bitcoin was by far the dominant cryptocurrency over the duration of the data used in this study, and most cryptocurrencies exhibited a high degree of correlation in terms of price dynamics, there still may be significant heterogeneity in sentiment across cryptocurrencies that may improve the explanatory power of the analyses conducted. As such, I would encourage future researchers to expand on this analysis by collecting and including on-chain transaction data of other cryptocurrencies into the calculation of the net unrealised profit and loss indicator.

The second limitation of this paper is that the period under study was during a time where most cryptocurrency trading occurred on centralised exchanges, and away from the on-chain framework. As such, the activity on the blockchain during that time may not be entirely representative of the cost basis of the cryptocurrencies, thus impacting the calculation of the $NUPL$ indicator. Hence, I would encourage future studies to obtain more recent data on trader activities to better assess and translate on-chain transactions into a dynamic sentiment indicator.

The third limitation of this study is related to the finding that NUPL is highly correlated with momentum. After controlling for momentum, I find that, while NUPL still captures some sentiment effects on traders' returns, the results are inconclusive. As such, I invite future research to dig deeper into relationships between NUPL and other macro factors.

Figure 4.1: The Natural Logarithm of Bitcoin Prices and the Net Unrealised Profit Loss from January 2012 to December 2021

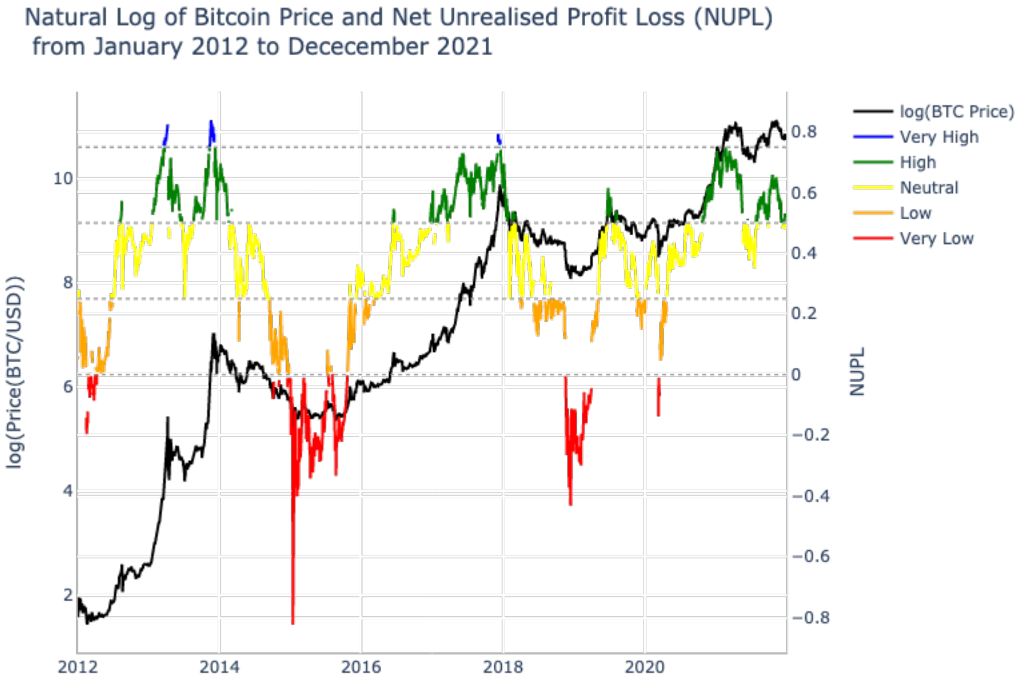

Figure 4.2: The Natural Logarithm of Bitcoin Price with Net Unrealised Profit Loss (NUPL) from January 2012 to December 2021 as a Superimposed Colour Indicator of Sentiment

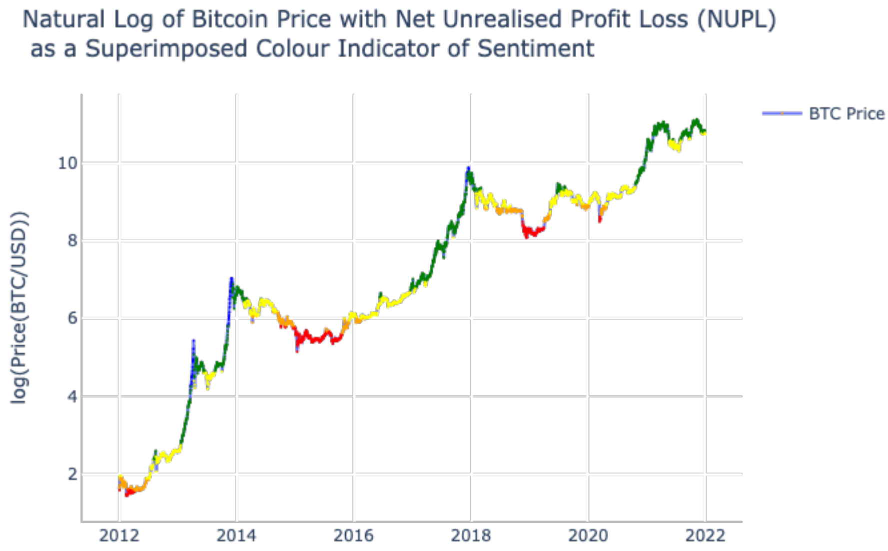

Figure 4.3: The Natural Logarithm of Bitcoin Prices and the Net Unrealised Profit Loss from June 2017 to December 2018

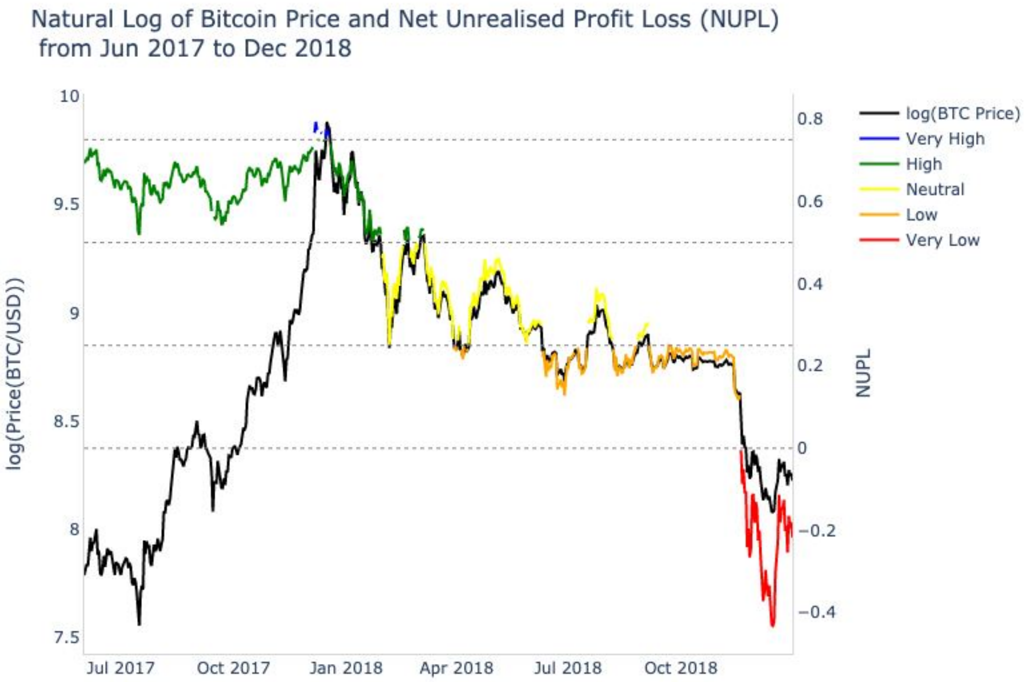

Figure 4.4: The Natural Logarithm of Bitcoin Price with Net Unrealised Profit Loss (NUPL) from June 2017 to December 2018 as a Superimposed Colour Indicator of Sentiment

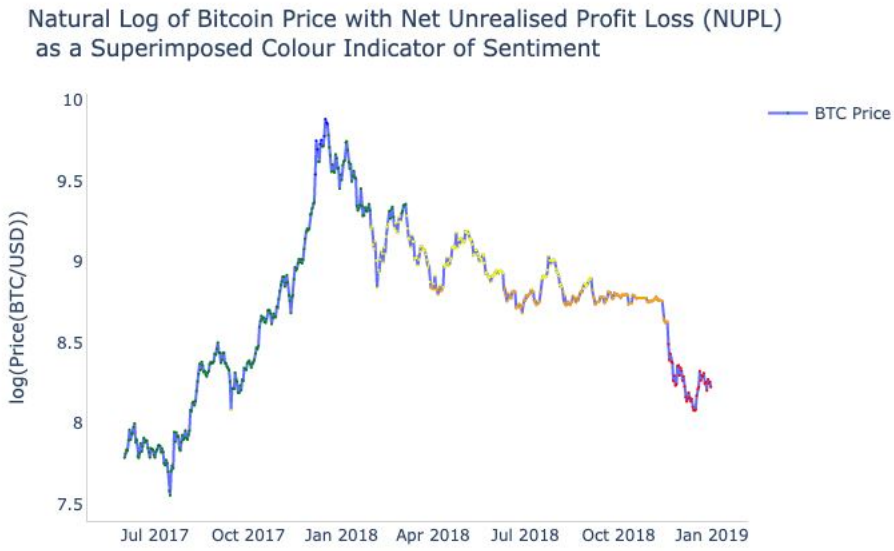

Figure 4.5: Cumulative Rolling Returns and NUPL

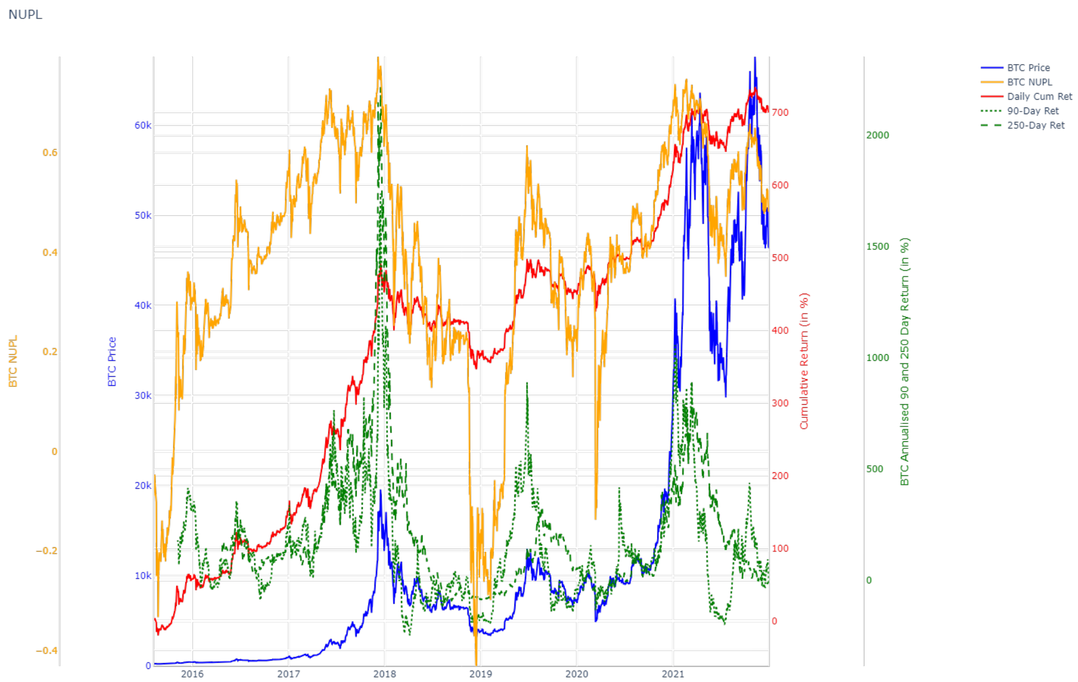

Figure 4.6: Cumulative Rolling Returns and NUPL from Jun 2017 to Dec 2018

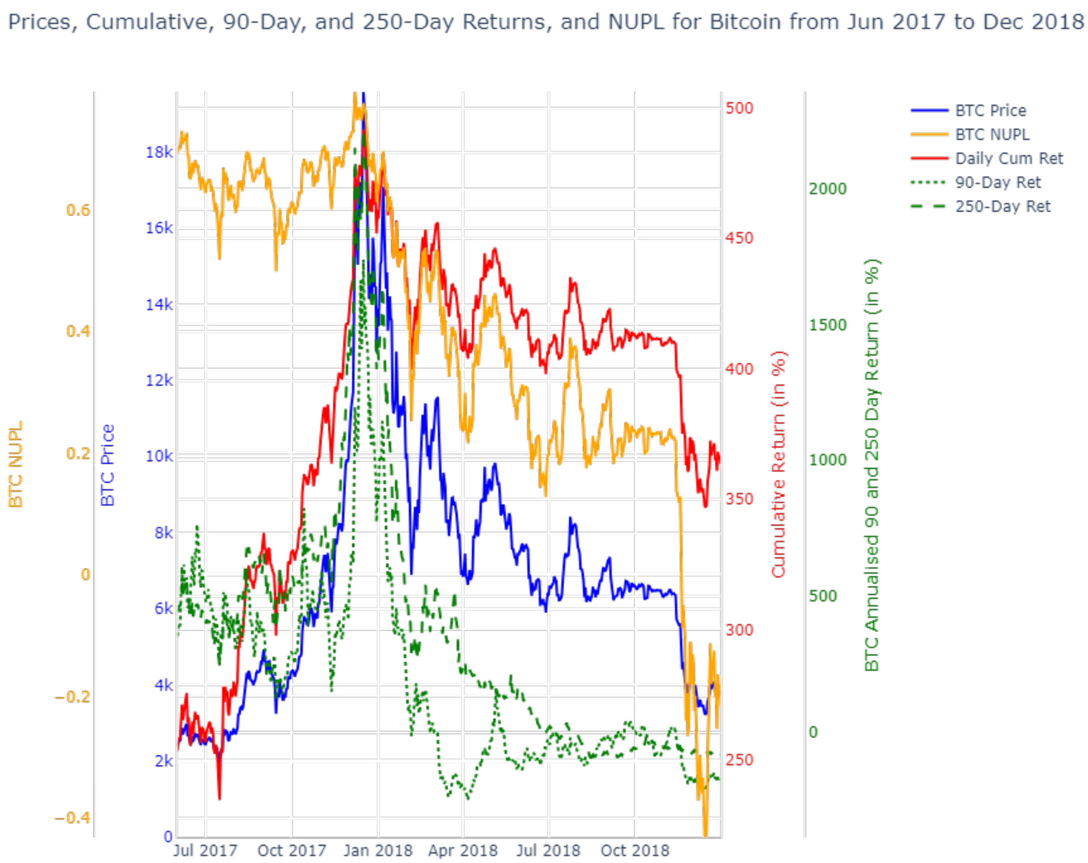

Table 4.1: Descriptive Statistics and Performance Measures of ExchangeX from June 2017 to December 2018. The following table shows descriptive statistics of traders on ExchangeX, as well as information on return on investment (Return) for traders on the platform. *Age of the Account* is the life of the account, *Age* is the age of the trader.
Number of Assets Traded is the number of assets the trader has used, *Number of Trades* is the number of trades filled and *Size of the Trade, USD* is the average size of a trade. *Return* shows the performance of market participants. $Return_{Unrealised}$ is the return component, which reflects the holding of inventory. $Return_{Realised}$ is the component that captures active portfolio management skills of a trader. $Return_{Total}$ is the sum of two components above. All *Return* metrics are in USD and on a daily basis.

Panel A: Trader Descriptive Statistics						
	Min.	**1st Q.**	**Mean**	**Median**	**3rd Q.**	**Max.**
Age of the Account, days	1	4	101	27	188	545
Age, years	20	29	37	34	41	71
Number of Assets Traded	2	2	3	3	3	65
Number of Trades	1	8	91	19	29	50,871
Size of the Trade, USD	1	14	489	201	409	620,021
Panel B: Return Metrics						
Return˙Unrealised, USD	-16.22%	-0.82%	0.23%	0.16%	0.56%	16.44%
Return˙Realised, USD	-8.54%	-1.69%	-0.76%	-0.45%	0.18%	5.98%
Return˙Total, USD	-16.22%	-0.67%	0.11%	0.16%	0.49%	15.26%

Table 4.2: The following table shows the results of Models 3.1.a and 3.1.b. The dependent variable is the $TotalROI$ for each trader on a weekly frequency. The independent variables for Model 3.1.a include the net unrealised profit loss for the Bitcoin Network, $NUPL$, as well as two lags of the change in $NUPL$, given by $\Delta NUPL$. The independent variables for Model 3.1.b include the categorical $Sentiment$ variable and its one-period lagged values. Both models include covariates for lagged realised performance, $RealisedROI$, and lagged log-volume, $log(Volume)$. Moreover, I include control variables for each trader that are estimated up to but not including time t such as the natural capitallogarithm of the average trade size, $log(AverageTrade)$, natural logarithm of the average balance size, $log(AverageBalance)$, cumulative number of trades executed, $NumberTrades$, number of unique markets traded, $NumberMarkets$, and lagged market volatility, $Volatility$, proxied by the standard deviation of hourly returns of BTC-USD. I control for demographics such as geographical, given by $Continent$, and age, denoted as Age. All models include trader and time fixed effects.

	Model (3.1.a)	Model (3.1.b)
$\Delta NUPL_{BTC,t,t-1}$	0.003^***(0.0001)	
$\Delta NUPL_{BTC,t-1,t-2}$	0.003^***(0.0001)	
$Sentiment_{VeryHigh,t}$		0.263^***(0.003)
$Sentiment_{High,t}$		0.197^***(0.003)
$Sentiment_{Neutral,t}$		0.132^***(0.003)
$Sentiment_{Low,t}$		0.107^***(0.002)
$Sentiment_{VeryHigh,t-1}$		0.301^***(0.003)
$Sentiment_{High,t-1}$		0.225^***(0.003)
$Sentiment_{Neutral,t-1}$		0.171^***(0.003)
$Sentiment_{Low,t-1}$		0.117^***(0.003)
$RealisedROI_{t-1}$	0.796^***(0.012)	0.807^***(0.011)
$RealisedROI_{t-2}$	-0.098^***(0.011)	-0.086^***(0.011)
$log(Volume)_{t-1}$	-0.001^***(0.0002)	-0.001^***(0.0002)
$log(Volume)_{t-2}$	-0.0004^*(0.0002)	-0.001^***(0.0002)
$log(AverageTrade)$	0.007^***(0.0004)	0.009^***(0.0004)
$log(AverageBalance)$	0.0001^***(0.00004)	0.0002^***(0.00004)
$NumberTrades$	-0.001^***(0.0001)	-0.001^**(0.0001)
$NumberMarkets$	0.001^***(0.0001)	0.002^***(0.0001)
$Volatility_{t-1}$	-0.0001^***(0.00001)	-0.0001^***(0.00001)
$Volatility_{t-2}$	-0.0001^***(0.00001)	-0.0001^***(0.00001)
$Age_{(30,40]}$	0.022 (0.017)	0.024 (0.018)
$Age_{(40,50]}$	0.015 (0.011)	0.016 (0.011)
$Age_{(50,60]}$	-0.011 (0.01)	-0.014 (0.011)
$Age_{(60+]}$	-0.36 (0.27)	-0.38 (0.27)
$Continent_{Americas}$	0.07 (0.056)	0.073 (0.06)
$Continent_{Asia}$	0.068 (0.053)	0.07 (0.057)
$Continent_{Europe}$	0.069 (0.057)	0.072 (0.059)
$Continent_{Oceania}$	0.057 (0.052)	0.06 (0.055)
R^2	21.8%	25.8%
Adjusted R^2	19.8%	23.9%
Note:		$^*p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table 4.3: The following table shows the results of Models 3.2.a and 3.2.b. The dependent variable is the $RealisedROI$ for each trader on a weekly frequency. The independent variables for Model 3.2.a include the net unrealised profit loss for the Bitcoin Network, $NUPL$, as well as two lags of the change in $NUPL$, given by $\Delta NUPL$. The independent variables for Model 3.2.b include the categorical $Sentiment$ variable and its one-period lagged values. Both models include covariates for lagged realised performance, $RealisedROI$, and lagged log-volume, $log(Volume)$. Moreover, I include control variables for each trader that are estimated up to but not including time t such as the natural logarithm of the average trade size, $log(AverageTrade)$, natural logarithm of the average balance size, $log(AverageBalance)$, cumulative number of trades executed, $NumberTrades$, number of unique markets traded, $NumberMarkets$, and lagged market volatility, $Volatility$, proxied by the standard deviation of hourly returns of BTC-USD. I control for demographics such as geographical, given by $Continent$, and age, denoted as Age. All models include trader and time fixed effects.

	Model (3.2.a)	Model (3.2.b)
$\Delta NUPL_{BTC,t,t-1}$	0.00004^**(0.00002)	
$\Delta NUPL_{BTC,t-1,t-2}$	0.00003^*(0.00002)	
$Sentiment_{VeryHigh,t}$		0.002^***(0.0004)
$Sentiment_{High,t}$		0.001^***(0.0004)
$Sentiment_{Neutral,t}$		0.001^**(0.0003)
$Sentiment_{Low,t}$		0.001^***(0.0003)
$Sentiment_{VeryHigh,t-1}$		-0.002^***(0.0004)
$Sentiment_{High,t-1}$		-0.002^***(0.0004)
$Sentiment_{Neutral,t-1}$		-0.001^***(0.0004)
$Sentiment_{Low,t-1}$		-0.001^***(0.0004)
$RealisedROI_{t-1}$	0.825^***(0.002)	0.825^***(0.002)
$RealisedROI_{t-2}$	-0.050^***(0.002)	-0.050^***(0.002)
$log(Volume)_{t-1}$	-0.00004(0.00003)	-0.00004(0.00003)
$log(Volume)_{t-2}$	-0.00001(0.00003)	-0.00001(0.00003)
$log(AverageTrade)$	0.0002^***(0.0001)	0.0002^***(0.0001)
$log(AverageBalance)$	0.00001^**(0.00001)	0.00001^**(0.00001)
$NumberTrades$	-0.001^***(0.0001)	-0.001^**(0.0001)
$NumberMarkets$	0.00004^***(0.00001)	0.00003^***(0.00001)
$Volatility_{t-1}$	-0.0001^***(0.00001)	-0.0001^***(0.00001)
$Volatility_{t-2}$	-0.0001^***(0.00001)	-0.0001^***(0.00001)
$Age_{(30,40]}$	0.009^***(0.001)	0.009^***(0.001)
$Age_{(40,50]}$	0.011^***(0.001)	0.011^***(0.001)
$Age_{(50,60]}$	0.01^***(0.001)	0.01^***(0.001)
$Age_{(60+]}$	0.008^***(0.001)	0.008^***(0.001)
$Continent_{Americas}$	0.032 (0.03)	0.032 (0.03)
$Continent_{Asia}$	0.03 (0.03)	0.03 (0.03)
$Continent_{Europe}$	0.042 (0.034)	0.042 (0.034)
$Continent_{Oceania}$	0.038 (0.032)	0.038 (0.032)
R^2	58.6%	58.9%
Adjusted R^2	58.1%	58.2%
Note:		$^*p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table 4.4: The following table shows the results of Models 3.3.a and 3.3.b. The dependent variable is the $log(Volume)$ for each trader on a weekly frequency. The independent variables for Model 3.3.a include the net unrealised profit loss for the Bitcoin Network, $NUPL$, as well as two lags of the change in $NUPL$, given by $\Delta NUPL$. The independent variables for Model 3.3.b include the categorical $Sentiment$ variable and its one-period lagged values. Both models include covariates for lagged realised performance, $RealisedROI$, and lagged log-volume, $log(Volume)$. Moreover, I include control variables for each trader that are estimated up to but not including time t such as the natural logarithm of the average trade size, $log(AverageTrade)$, natural logarithm of the average balance size, $log(AverageBalance)$, cumulative number of trades executed, $NumberTrades$, number of unique markets traded, $NumberMarkets$, and lagged market volatility, $Volatility$, proxied by the standard deviation of hourly returns of BTC-USD. I control for demographics such as geographical, given by $Continent$, and age, denoted as Age. All models include trader and time fixed effects.

	Model (3.3.a)	Model (3.3.b)
$\Delta NUPL_{BTC,t,t-1}$	0.002^***(0.001)	
$\Delta NUPL_{BTC,t-1,t-2}$	0.001(0.001)	
$Sentiment_{VeryHigh,t}$		0.198^***(0.019)
$Sentiment_{High,t}$		0.117^***(0.018)
$Sentiment_{Neutral,t}$		0.043^**(0.018)
$Sentiment_{Low,t}$		0.021(0.017)
$Sentiment_{VeryHigh,t-1}$		0.165^***(0.021)
$Sentiment_{High,t-1}$		0.080^***(0.020)
$Sentiment_{Neutral,t-1}$		0.052^***(0.020)
$Sentiment_{Low,t-1}$		0.014(0.019)
$RealisedROI_{t-1}$	-0.207^***(0.080)	-0.205^**(0.080)
$RealisedROI_{t-2}$	-0.061(0.077)	-0.064(0.077)
$log(Volume)_{t-1}$	-0.711^***(0.002)	-0.711^***(0.002)
$log(Volume)_{t-2}$	-0.045^***(0.001)	-0.045^***(0.001)
$log(AverageTrade)$	-0.036^***(0.003)	-0.037^***(0.003)
$log(AverageBalance)$	0.001^**(0.0003)	0.001^***(0.0003)
$NumberTrades$	-0.002^***(0.0001)	-0.002^**(0.0001)
$NumberMarkets$	-0.00007^***(0.00001)	-0.00007^***(0.00001)
$Volatility_{t-1}$	-0.0001^***(0.00001)	-0.0001^***(0.00001)
$Volatility_{t-2}$	-0.0001^***(0.00001)	-0.0001^***(0.00001)
$Age_{(30,40]}$	0.055^***(0.015)	0.056^***(0.015)
$Age_{(40,50]}$	-0.022 (0.02)	-0.022 (0.02)
$Age_{(50,60]}$	-0.02 (0.02)	-0.02 (0.02)
$Age_{(60+]}$	-0.14^***(0.05)	-0.14^***(0.05)
$Continent_{Americas}$	0.197^***(0.07)	0.197^***(0.07)
$Continent_{Asia}$	0.206^***(0.071)	0.206^***(0.071)
$Continent_{Europe}$	0.18^***(0.068)	0.18^***(0.068)
$Continent_{Oceania}$	0.227^***(0.075)	0.228^***(0.075)
R^2	60.1%	60.2%
Adjusted R^2	59.8%	59.9%
Note:		*p<0.1; **p<0.05; ***p<0.01

Table 4.5: The following table shows the results of Models 3.4.a and 3.4.b. The dependent variable is the $\Delta log(Volume)$ for each trader on a weekly frequency. The independent variables for Model 3.4.a include the net unrealised profit loss for the Bitcoin Network, $NUPL$, as well as two lags of the change in $NUPL$, given by $\Delta NUPL$. The independent variables for Model 3.4.b include the categorical $Sentiment$ variable and its one-period lagged values. Both models include covariates for lagged realised performance, $RealisedROI$, and lagged log-volume, $log(Volume)$. Moreover, I include control variables for each trader that are estimated up to but not including time t such as the natural logarithm of the average trade size, $log(AverageTrade)$, natural logarithm of the average balance size, $log(AverageBalance)$, cumulative number of trades executed, $NumberTrades$, number of unique markets traded, $NumberMarkets$, and lagged market volatility, $Volatility$, proxied by the standard deviation of hourly returns of BTC-USD. I control for demographics such as geographical, given by $Continent$, and age, denoted as Age. All models include trader and time fixed effects.

	Model (3.4.a)	Model (3.4.b)
$\Delta NUPL_{BTC,t,t-1}$	0.063(0.067)	
$\Delta NUPL_{BTC,t-1,t-2}$	0.010(0.069)	
$Sentiment_{VeryHigh,t}$		1.612(1.538)
$Sentiment_{High,t}$		1.614(1.440)
$Sentiment_{Neutral,t}$		1.468(1.391)
$Sentiment_{Low,t}$		-0.060(1.338)
$Sentiment_{VeryHigh,t-1}$		-0.510(1.682)
$Sentiment_{High,t-1}$		-0.751(1.589)
$Sentiment_{Neutral,t-1}$		-0.884(1.544)
$Sentiment_{Low,t-1}$		-0.032(1.460)
$RealisedROI_{t-1}$	-0.097^***(0.020)	-0.097^***(0.020)
$RealisedROI_{t-2}$	-0.063^***(0.010)	-0.064^***(0.010)
$log(Volume)_{t-1}$	-0.212^*(0.126)	-0.210^*(0.126)
$log(Volume)_{t-2}$	-0.083 (0.117)	-0.082 (0.117)
$log(AverageTrade)$	-0.068 (0.200)	-0.059 (0.200)
$log(AverageBalance)$	0.01^***(0.003)	0.01^***(0.003)
$NumberTrades$	-0.001^***(0.0003)	-0.001^***(0.0003)
$NumberMarkets$	-0.014^***(0.002)	-0.011^***(0.002)
$Volatility_{t-1}$	-0.0001^***(0.00001)	-0.0004^***(0.00001)
$Volatility_{t-2}$	-0.0001^***(0.00001)	-0.0004^***(0.00001)
$Age_{(30,40]}$	0.043^**(0.023)	0.044^**(0.023)
$Age_{(40,50]}$	-0.036 (0.03)	-0.036 (0.03)
$Age_{(50,60]}$	-0.035 (0.03)	-0.036 (0.03)
$Age_{(60+]}$	-0.11^***(0.02)	-0.11^***(0.02)
$Continent_{Americas}$	0.13^***(0.03)	0.131^***(0.03)
$Continent_{Asia}$	0.137^***(0.03)	0.137^***(0.03)
$Continent_{Europe}$	0.133^***(0.03)	0.133^***(0.03)
$Continent_{Oceania}$	0.126^***(0.02)	0.126^***(0.02)
R^2	50.3%	50.3%
Adjusted R^2	50.0%	50.1%

Note: *p<0.1; **p<0.05; ***p<0.01

Table 4.6: The following table shows the produced correlation analysis between variables.

	NUPL_BTC	NUPL_pct_chng_day	NUPL_pct_chng_week	price˙BTC	BTC_1D_ret	BTC_1W_ret	BTC_30D_ret	BTC_60D_ret	BTC_90D_ret	BTC_180D_ret	BTC_250D_ret	cum_sum_1D_ret
NUPL_BTC	100%	-5.34%	-2.68%	43.65%	10.29%	25.93%	45.56%	57.97%	64.13%	67.86%	60.00%	36.38%
NUPL_pct_chng_day	-5.34%	100%	-0.15%	-1.50%	-0.11%	-5.78%	-3.39%	-2.91%	-2.36%	-2.61%	-2.31%	-0.30%
NUPL_pct_chng_week	-2.68%	-0.16%	100%	-0.57%	-0.76%	-0.00%	-0.38%	-0.63%	-0.69%	-0.79%	-0.63%	-0.89%
price˙BTC	43.65%	-1.50%	-0.57%	100%	0.61%	2.17%	5.74%	12.37%	19.87%	25.43%	19.85%	78.95%
BTC_1D_ret	10.30%	-0.11%	-0.75%	0.61%	100%	39.69%	17.76%	15.00%	12.31%	6.82%	7.38%	-0.06%
BTC_1W_ret	25.94%	-5.78%	-0.04%	2.17%	39.69%	100%	49.67%	37.75%	33.42%	18.97%	20.41%	0.26%
BTC_30D_ret	45.56%	-3.39%	-0.38%	5.74%	17.76%	49.67%	100%	74.69%	66.33%	43.24%	45.50%	1.07%
BTC_60D_ret	57.97%	-2.92%	-0.64%	12.37%	15.00%	37.75%	74.69%	100%	85.97%	64.01%	61.56%	4.10%
BTC_90D_ret	64.13%	-2.37%	-0.70%	19.19%	12.31%	33.42%	66.33%	85.97%	100%	78.93%	71.00%	8.14%
BTC_180D_ret	67.87%	-2.61%	-0.79%	25.43%	6.82%	18.97%	43.24%	64.01%	78.93%	100%	88.27%	13.66%
BTC_250D_ret	60.00%	-2.31%	-0.63%	19.85%	7.38%	20.41%	45.50%	61.56%	71.00%	88.27%	100%	11.53%
cum_sum_1D_ret	36.39%	-0.30%	-0.88%	78.95%	-0.06%	0.26%	1.07%	4.10%	8.14%	13.66%	11.53%	100%

Table 4.7: The following table shows the results of Model 3.2.b. The dependent variable is the *RealisedROI* for each trader on a weekly frequency. The independent variables for Model 3.2.b include residuals, categorised into 5 categories. Both models include covariates for lagged realised performance, *RealisedROI*, and lagged log-volume, $log(Volume)$. Moreover, I include control variables for each trader that are estimated up to but not including time t such as the natural logarithm of the average trade size, $log(AverageTrade)$, natural logarithm of the average balance size, $log(AverageBalance)$, cumulative number of trades executed, $NumberTrades$, number of unique markets traded, $NumberMarkets$, and lagged market volatility, $Volatility$, proxied by the standard deviation of hourly returns of BTC-USD. I control for demographics such as geographical, given by *Continent*, and age, denoted as *Age*. All models include trader and time fixed effects.

	Model (3.2.b)
$VIXcat2$	-0.000003285(0.000002971)
$VIXcat3$	-0.000004864(0.000003218)
$VIXcat4$	0.0000007626(0.000003128)
$VIXcat5$	-0.000001347(0.00000284)
$RealisedROI_{t-1}$	0.993ˆ***(0.000269)
$RealisedROI_{t-2}$	-0.001526ˆ***(0.00026842)
$log(Volume)_{t-1}$	-0.0000007647(0.000005141)
$log(Volume)_{t-2}$	-0.0000002716(0.000005115)
$log(AverageTrade)$	0.000007225ˆ***(0.000001833)
$log(AverageBalance)$	0.0000003966ˆ*(0.0000001983)
$NumberTrades$	-0.0000000232ˆ***(0.000000002915)
$NumberMarkets$	0.00000192ˆ***(0.0000002635)
$Volatility_{t-1}$	0.00000006514ˆ***(0.000000007781)
$Volatility_{t-2}$	-0.0001ˆ***(0.00001)
$Age_{(30,40]}$	0.0089ˆ***(0.001)
$Age_{(40,50]}$	0.012ˆ***(0.001)
$Age_{(50,60]}$	0.01ˆ***(0.001)
$Age_{(60+]}$	0.009ˆ***(0.001)
$Continent_{Americas}$	0.031 (0.03)
$Continent_{Asia}$	0.03 (0.03)
$Continent_{Europe}$	0.041 (0.034)
$Continent_{Oceania}$	0.038 (0.032)
R^2	58.1%
Adjusted R^2	57.7%

Note: *p<0.1; **p<0.05; ***p<0.01

Table 4.8: The following table shows the results of Model 3.2.b. The dependent variable is the *RealisedROI* for each trader on a weekly frequency. The independent variables for Model 3.2.b include the equity volatility index VIX, categorised into 5 categories. Both models include covariates for lagged realised performance, *RealisedROI*, and lagged log-volume, $log(Volume)$. Moreover, I include control variables for each trader that are estimated up to but not including time t such as the natural logarithm of the average trade size, $log(AverageTrade)$, natural logarithm of the average balance size, $log(AverageBalance)$, cumulative number of trades executed, *NumberTrades*, number of unique markets traded, *NumberMarkets*, and lagged market volatility, *Volatility*, proxied by the standard deviation of hourly returns of BTC-USD. I control for demographics such as geographical, given by *Continent*, and age, denoted as *Age*. All models include trader and time fixed effects.

	Model (3.2.b)
$Residualscat2$	-0.00006493^***(0.00001401)
$Residualscat3$	-0.00001937(0.0000162)
$Residualscat4$	-0.00005059^**(0.00001618)
$Residualscat5$	-0.00001518(0.00001892)
$RealisedROI_{t-1}$	0.9723^***(0.0005921)
$RealisedROI_{t-2}$	-0.006969^***(0.0005873)
$log(Volume)_{t-1}$	-0.00000867(0.00001147)
$log(Volume)_{t-2}$	-0.000002999(0.00001126)
$log(AverageTrade)$	0.00004019^***(0.000007493)
$log(AverageBalance)$	0.000001836^*(0.0000008596)
$NumberTrades$	-0.00000008639^***(0.00000001208)
$NumberMarkets$	0.000006754^***(0.00000101)
$Volatility_{t-1}$	0.0000002278^***(0.00000004526)
$Volatility_{t-2}$	-0.0001^***(0.00001)
$Age_{(30,40]}$	0.0089^***(0.001)
$Age_{(40,50]}$	0.01^***(0.001)
$Age_{(50,60]}$	0.01^***(0.001)
$Age_{(60+]}$	0.009^***(0.001)
$Continent_{Americas}$	0.03 (0.03)
$Continent_{Asia}$	0.029 (0.03)
$Continent_{Europe}$	0.04 (0.03)
$Continent_{Oceania}$	0.037 (0.03)
R^2	57.9%
Adjusted R^2	57.6%

Note: *p<0.1; **p<0.05; ***p<0.01

Chapter 5

Conclusion and Future Work

Chapter 5

Conclusion and Future Work

The contributions of this thesis are both theoretical and empirical.

In the first study, I investigate the disposition effect among cryptocurrency traders on a centralised crypto exchange using data spanning from June 2017 to December 2018. I apply the disposition spread of Odean (1998) and find significant evidence of an anti-disposition effect. The research also examines the impact of market conditions, trading experience, and age demographics on the disposition effect within the cryptocurrency market, concluding that market movements and the size of trades do not substantially influence the propensity of traders to secure profits or endure losses. Notably, the 18-30 age bracket shows a distinctive positive disposition effect, pointing to a faster rate of profit-taking. In contrast, the disposition effect diminishes among older traders, suggesting they are less prone to cling to depreciating assets as they age. This observation is in harmony with existing studies which suggest that accrued trading experience tends to reduce cognitive biases, a trend that holds true across both digital and traditional financial marketplaces.

In the second study, I examine whether crypto traders exhibit the gambler's fallacy or the hot hand fallacy by measuring how past performance impacts future trader decisions. My findings show that individuals are likely to increase their position size after exhibiting poor past performance, and likely to trade in the direction opposite to how the market has been trending. These results support the prevalence of the gambler's fallacy among cryptocurrency traders, whereby individuals are likely to increase the size of their trades after realising poor performance. This occurs as traders strive to make up for poor past decisions. Moreover, crypto traders believe in mean reversion of crypto prices, as they bet that the most recent price trend will reverse following their subsequent trade. These findings are of interest to academics, practitioners, and traders, as they highlight the tendency of traders to succumb to the gambler's fallacy, which has been documented to negatively impact trader performance. Consequently, traders may learn to avoid making decisions based on short-term trend reversals and instead invest based on fundamental information.

In the third and final study, I investigate whether and how market sentiment impacts the performance and trading activity of crypto traders. Using a novel blockchain-based sentiment indicator, called the Net Unrealised Profit Loss or $NUPL$, as an alternative to the text-based models used in the literature, I show that sentiment positively impacts the total return experienced by traders, whereby the highest levels of total returns occur when market sentiment is at its highest. Second, while higher levels of, and changes in lagged sentiment values lead to higher realised returns, this effect is relatively small. Nonetheless, traders who react promptly to market sentiment especially when sentiment is very high, are likely to realise higher positive returns. Finally, I show that traders have larger trade sizes when market sentiment is high; however, they do not necessarily alter their trade size based on market sentiment. To ensure robustness, the study employed the VIX index to measure sentiment in the cryptocurrency market and found it ineffective in predicting the realised ROI, suggesting the need for a crypto-specific sentiment metric. Additionally, while NUPL correlates with overall market sentiment, it doesn't solely influence short-term trading decisions, indicating that sentiment and price momentum may affect trading behaviour independently.

This thesis highlights how certain behavioural biases as well as market sentiment impact crypto trader performance and activity. The findings I present differ in some respects to what has been documented in financial literature on traditional markets. Hence, one may conclude that the technological innovation that is fuelling the crypto market, as well as the anonymity and decentralisation of this novel asset class contribute to differentials in trading behaviours among retail traders.

I briefly conclude this thesis by discussing some future work I aim to undertake. Another popular behavioural bias in financial literature that has been linked to poor performance is herding behaviour. Using the transaction data used in this study and herding measures designed specifically for trade-level data, I plan on measuring the degree of herding behaviour in crypto markets, and test whether such behaviour persists to the extent where it can propagate short term trends in prices. This analysis will contribute to the literature on herding behaviour in crypto markets, which has mainly adopted regression models to estimate price deviations as a proxy for herding behaviour.

Moreover, I plan to use methodologies developed for event analysis in order to examine whether and to what extent trader performance and behaviour changes given specific crypto ban events as well as crypto-related Tweets by prominent business leaders, such as Elon Musk. This analysis will help shed light on how retail crypto traders ingest and execute on news and opinions in a market that lacks sufficient fundamental information. The findings of such an analysis will have regulatory implications, given that published opinions by certain individuals or entities may significantly impact the prices of these unregulated and anonymous digital assets.

A compelling task for future research is to include data from decentralised exchanges, which have witnessed significant growth over the past year due to the innovations in blockchain technology, which have made on-chain transactions much more affordable. As such, it would be interesting to investigate whether trader behaviour differs depending on the degree of centralisation of the venue within which they are operating.

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