Sentiment and Trading Decisions in an Ambiguous Environment: A Study on Cryptocurrency Traders*

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Abstract

The role of public sentiment in traders' decision-making is potentially more pronounced in crypto-asset markets, given a lack of quantifiable financial fundamental information and historical precedent for pricing behaviour. Using a data set of over two million transactions executed on a cryptocurrency exchange, we test the extent to which sentiment conveyed within cryptocurrency communities on Reddit impacts upon the performance, deposit and withdrawal behaviour, and position exposure of cryptocurrency traders. Our evidence supports the notion that sentiment plays a role in the investment decision-making process. Traders tend to realise positive returns when sentiment is bullish. Moreover, positive changes in the level of bullishness lead to traders executing larger trades, and a higher probability of depositing and withdrawing funds. Measures such as the degree of consensus within the online crowd, readership size and contributor reputation produce less compelling results, but offer some insights into Reddit community dynamics.

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Competing interests statement

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1. Introduction

Cryptocurrencies have generated enormous levels of talk and enthusiasm in recent years, with public discourse dominated by narratives of bubbles, anarchism, human-interest and fear of inequality. Shiller (2020) summarises the narratives surrounding cryptocurrency innovations, building on earlier assertions that news media drives sentiment and sets the stage for market movements (Shiller, 2015). These narratives play an important role in determining the popularity of cryptocurrencies given the "general lack of traditional quantifiable financial fundamentals that underpin crypto-asset valuations" (Gurdgiev and O'Loughlin, 2020, p. 2). Additionally, since crypto-asset markets and underlying technologies are still in the development phase, there exists little historical precedent for pricing behaviour. The market for cryptocurrencies is therefore ambiguous, as future probabilities do not capture historical events. These factors point to the heightened importance of observable public sentiment in the price discovery process for cryptocurrencies in comparison to traditional assets. More succinctly, cryptocurrencies such as Bitcoin "have value today because of public excitement" (Shiller, 2020, p. 4). In this respect, conversations about cryptocurrencies are occasionally grounded in the context of historical speculative events (Chen and Hafner, 2019) such as the "tulip mania" observed in the Netherlands during the 1630s.

The determinants of cryptocurrency traders' decision to trade and, more specifically, the extent to which those traders rely on sentiment in the absence of fundamental information, are yet to be fully established. Recent studies have explored the extent to which variables such as macro-financial indicators (Ciaian et al., 2016), economic policy uncertainty (Demir et al., 2018), and the volume of internet searches (Nasir et al., 2019) impact cryptocurrency pricing and trading activity at the aggregate market level. Likewise, studies on text-based sentiment via social media platforms, such as *Twitter* (Guégan and Renault, 2020) and

Reddit (Nasekin and Chen, 2020), have shown evidence of potential ramifications on the price-discovery process. These findings in particular have been supported by recent market events such as the appreciation of the cryptocurrency *Dogecoin* by 800% relative to the U.S. Dollar over a twenty-four hour period; an event widely attributed to collective action facilitated by the Reddit platform (Kharpal, 2021).

Despite recent evidence that sentiment influences cryptocurrency returns at the market level, little research has been conducted on the effects of sentiment on decision-making at the individual trader level. We therefore address the extent to which measures of online sentiment, such as community bullishness, consensus and audience size impact upon traders' performance, their cryptocurrency exposure (size of trade), and the frequency and size with which they deposit or withdraw funds from their account. Specifically, we utilise a unique data set of over two million transactions by more than 20,000 traders executed on a cryptocurrency exchange, in order to investigate the extent to which market sentiment influences decision-making in an environment governed by anonymity of participants and ambiguity of the asset class. As a proxy for market sentiment, we construct sentiment indices by applying supervised machine learning techniques on 1.2 million cryptocurrency-related submissions posted to the online platform Reddit. Our research thus contributes to the literature addressing the role of text-based sentiment in the decision-making process of cryptocurrency market agents, and of financial market agents more broadly.

We use panel regression models to test the relationship between online community discussion and cryptocurrency trader activity, including control variables that quantify the level of online sentiment, agreement, audience and peer-assigned "credibility" of content published on the Reddit platform. We also include trader-specific parameters such as a trader's prior performance, cumulative number of trades, count of unique assets traded, average trade size and average balance. Moreover, we control for demographics including country of residence and age. Our results indicate that trader performance is positively associated with online community sentiment. Further, the likelihood with which traders deposit and withdraw funds increases during periods of prevalent sentiment, and the size of deposits decreases during such periods. We argue that this is the result of investors placing infrequent and heavy bets during periods where sentiment is lower, and thus when cryptocurrencies may be perceived as being "undervalued".

The extent to which traders' decision-making is influenced by community consensus amongst Reddit contributors is less clear. Similarly, we find little compelling evidence to suggest that the credibility assigned to Reddit submissions, and the potential readership/audience size, have any significant effects on trader behaviour. Our research builds on previous work suggesting statistically significant (albeit economically small) returns following changes in the level of online sentiment (Guégan and Renault, 2020; Valencia et al., 2019; Abraham et al., 2018). The remainder of this paper is structured as follows. Section 2 provides an overview of the relevant literature. Section 3 presents the methodology. Section 4 describes the two data sets used. Section 5 analyses the results, before Section 6 concludes.

2. Relevant Literature

Associations between online investor community discussions and investor decision-making are expected to some extent, given that financial communities and exchanges provide a vehicle for social integration as well as economic exchange (Baker, 1984). That is, "financial markets live on gossip" (Mainelli, 2003, p. 629), both online and offline. In the offline environment, analyst "whisper forecasts" have been found to be a more accurate predictor of quarterly announced earnings than professional forecasts (Bagnoli et al., 1999),[1]. However, it is difficult to accurately capture conversations in the offline environment, and thus the emergence of online communities in recent years offers a valuable real-time window (Das et al., 2005) through which to observe investor behaviour within collaborative and information-dense communities (O'Connor, 2013). De Jong et al. (2017) note that between 34 and 70 percent of investors utilise social media content in their investment decision making, while there is evidence to suggest that online stock prediction communities outperform professional analysts (Nofer and Hinz, 2015).

Aided by a geometric increase in the amount of textual data (Nardo et al., 2016), and based on an underlying assumption that "movements in financial markets and movements in news are intrinsically interlinked"(Alanyali et al., 2013, p. 1), the most common exploration test is the level of correlation between the degree of positive or negative sentiment conveyed in qualitative content (such as social media postings) and market activity in the underlying asset subject to discussion (Renault, 2020). Often, such research serves to identify whether positive or negative signals observed in this qualitative content constitute new information which can subsequently be incorporated into the price-discovery process, or whether prior market events influence the sentiment with which a company or asset class is discussed. Although significant correlations in both respects are identified in prior studies (Loughran and McDonald, 2016), the application of textual analysis techniques to investment discussions has been a gradual process and thus the literature is still developing.

The allocation of sentiment scores to financial texts is often conducted using domain-specific dictionaries, which assign words into positive, neutral, or negative categories. The

[1]It should be noted that Brown Jr and Fernando (2011) find the opposite to be the case in more recent years, although whisper forecasts still play a complementary role in providing information about the firm.

sentiment assigned to a text is therefore a product of the frequency with which words from each category appear (Kearney and Liu, 2014). For example, Chen et al. (2014) apply the Loughran and McDonald (2011) dictionary to user-generated articles published on the *SeekingAlpha* platform, and find that the fraction of negative words used in published articles negatively predicts stock returns over the ensuing three months. Controlling for well-known trading patterns, Garcia (2013) applies the same dictionary to financial articles printed in the *New York Times*, finding that a one standard deviation shock to the level of media pessimism moves the Dow Jones Industrial Average by 12 basis points during recessionary periods. (Corbet et al., 2020) employ a similar dictionary technique and identify cryptocurrency returns to be significantly influenced by the degree of negative *Twitter* sentiment related to the COVID-19 pandemic. Chen et al. (2019) construct a crypto-specific dictionary of positive and negative words using message posted on the social media platform *StockTwits*, which Liu and Tsyvinski (2021) apply to *Google* searches. In doing so, the authors find that sentiment positively and significantly predicts cryptocurrency returns.

Supervised machine learning techniques are also regularly employed to infer the sentiments contained in online financial discussion (Li, 2010). For example, Antweiler and Frank (2004) apply a Naive Bayes classifier to a data set of 1.6 million message board postings and find that a one unit increase in community bullishness on a given day doubles the probability of an article in the *Wall Street Journal* the following day, implying that financially relevant information is present in online message board discussion, although it is much noisier and less reliable. Sprenger et al. (2014) apply a similar classifier to a data set of stock-related messages on social media platform *Twitter* and find significant contemporary associations between tweet bullishness and abnormal returns. Those online users who generate above-average advice are given credit and a greater voice within the community, through a higher level of "retweets" and followers. The authors also find positive associations between the level of online disagreement - measured as the degree of variance in tweet sentiment - and trade volatility, building on the earlier finding of Antweiler and Frank (2004) that disagreement is associated with a higher level of trading activity. Such evidence is consistent with prior models – such as that of Harris and Raviv (1993) – predicting that traders receive common information but differ in their interpretation, with resulting uncertainty leading to higher trade volumes.

More recently, deep learning-based sentiment measures have been utilised in academic research. For example, Nasekin and Chen (2020) use recurrent neural networks (RNNs) to create sentiment indices based on user contributions to *StockTwits* and find that sentiment significantly contributes to the predictability of cryptocurrency log-returns, while Chen and Hafner (2019) derive sentiment from contributions to the social media platform *StockTwits* and find that volatility in cryptocurrency pricing increases as sentiment decreases.[2]

The application of textual sentiment techniques to crypto-specific discussion is comparatively limited in relation to more traditional asset classes. To some extent, this is because cryptocurrencies are relatively new, with the first (Bitcoin) emerging in 2009. Over 1,400 cryptocurrencies are now circulating worldwide (Lee, 2019), but compared to established markets (such as equities, debt and commodities), cryptocurrency markets are considered to be still in their infancy (Phillip et al., 2018). Nasekin and Chen (2020) discuss the challenges facing classical asset pricing theories following the emergence of new cryptocurrencies, whose fundamental values can be difficult to measure. Underlying technologies and techniques, such as blockchain, initial coin offerings (ICOs) and decentralised schemes, further complicate fair

[2]Application of deep learning models in the finance domain is still relatively new and there exists some debate about the extent to which more computationally demanding methods improve classifier accuracy when analysing informal texts (Renault, 2020).

price estimation. This potentially indicates a more pronounced role of online public sentiment in price formation, when compared to traditional assets. Indeed, Guégan and Renault (2020) find significant (albeit economically small) associations between investor sentiment and Bitcoin returns for intra-day frequencies of up to fifteen minutes. Using tweet volumes and *Google Trends* index levels as proxies for public interest, Abraham et al. (2018) find high levels of association with cryptocurrency prices, while Valencia et al. (2019) construct sentiment indices using *Twitter* content and identify a degree of price prediction accuracy above 50% for certain cryptocurrencies (such as Bitcoin, Ethereum, Ripple and Litecoin).

3. Methodology

Extracting key themes from the literature we find support for the idea that the level of sentiment conveyed via online media platforms has implications on asset pricing and underlying trading activity; specifically, positive sentiment is associated with positive abnormal returns. (Liu and Tsyvinski, 2021; Corbet et al., 2020; Garcia, 2013). Relationships are also identified between the level of online disagreement expressed online (variance in sentiment) and trade activity (Sprenger et al., 2014; Antweiler and Frank, 2004), while others suggest that both the credibility of online user-generated content (Depken and Zhang, 2010) and the size of the audience who observe online signals (Mai et al., 2018) have implications on the magnitude of association. Though such studies suggest that online sentiment has implications at the market level, to our knowledge no such research has been conducted at the trader level. Building on earlier studies, we use a proprietary dataset of individual trades placed via a large cryptocurrency exchange to investigate the extent to which online sentiment is associated with traders' behaviour. Specifically, we seek to examine the extent to which the level of sentiment conveyed within online cryptocurrency community discussions is associated with (i) the performance of cryptocurrency traders, measured in the context of their realised, unrealised and total profit; (ii) the level of exposure that traders are willing to accept, in terms of how much they invest in each trade; (iii) the traders' likelihood of depositing funds into their cryptocurrency accounts, and the amount deposited; and (iv) the likelihood of withdrawing funds from their cryptocurrency account, and the amount withdrawn. The following section details the methods used to calculate the various sentiment and performance measures.

3.1. Quantifying Sentiment

Reddit is selected as the chosen platform on which to base our sentiment metrics due to the public availability of contributions ('submissions') and as a large user base.[3] The Reddit platform uses subreddits to distinguish between different topics.[4] Thus, the likelihood of excluding relevant interactions (and including irrelevant ones) is reduced. Further, the ability for collective action facilitated by Reddit to impact on financial markets has been recently demonstrated by an increase in *GameStop Corporation* shares of 1,700% within a one month period, which was largely attributed to "retail traders coordinating on Reddit message boards" (Aliaj et al., 2021).

We use a Naive Bayes 'bag of words' classifier to derive sentiment from each submission on the basis that it is well established and "simple classifiers...will often do the trick for social media sentiment analysis" (Renault, 2020, p. 9). The classifier assigns a sentiment score of +1 (positive, or "buy"), 0 (neutral, or "hold"), or -1 (negative, or "sell") to each unique submission. Using these scores, we calculate weekly aggregated Reddit sentiment

[3]Glenski et al. (2019) note there to be 330 million users active in 140 thousand communities ('subreddits'), who post 2.8 million comments daily.

[4]For example, if a member wished to contribute to general cryptocurrency discussion, they would publish their submission (authored contribution) within the *r/Cryptocurrency* subreddit.

using a modified version of the "bullishness" ratio (Zhang, 2014) originally developed by Antweiler and Frank (2004).[5] Given the number of submissions expressing positive sentiment ($M_t^{i,BUY}$), neutral sentiment ($M_t^{i,HOLD}$), and negative sentiment ($M_t^{i,SELL}$), we calculate weekly bullishness (B_t^i) as:

$$B_t^i = \frac{R_t^i - 1}{R_t^i + 1 + \frac{M_t^{i,HOLD}}{M_t^{i,SELL}}} \tag{1}$$

where R_t^i represents the ratio of bullish to bearish submissions ($R_t^i = M_t^{i,BUY}/M_t^{i,SELL}$).

We also extract the number of 'up-votes' (similar to the *like* feature commonly found on social media platforms such as *Facebook*) that a submission attracts from the community (*ThumbsUp*), and the number of members subscribed to the subreddit at the time in which the submission was posted (*Subscribers*). We use *ThumbsUp* as a proxy for credibility (reputation) on the basis that in an environment in which talk is 'cheap', even small pecuniary rewards such as 'up-votes' can significantly reduce the temptation to convey extreme sentiment (or 'hyping'), leading to more informational and nuanced content (Depken and Zhang, 2010).[6] As a result, any associations between sentiment and trading activity may be pronounced during periods when the natural logarithm of *ThumbsUp* is higher. We also proxy for readership (audience size) using the natural logarithm of *Subscribers*, on the basis that Mai et al. (2018) find social media effects on cryptocurrency markets to be primarily driven by a 'silent majority' of online users, and discussions induce trading from 'side-lined

[5]Whereas Antweiler and Frank (2004) discount those submissions classified as neutral (hold) sentiment in the denominator of Equation 1, Zhang (2014) argues that neutral, or hold, submissions should not be excluded in aggregate sentiment scores.

[6]Depken and Zhang (2010) find that authors with no reputation convey positive or negative sentiment more frequently, whereas authors with a higher reputation offer comparatively more neutral or muted sentiment.

investors' who trade on observed signals (Cao et al., 2002).

Associations between disagreement and trading volume in equities are well documented (Hong and Stein, 2007). We employ Antweiler and Frank (2004)'s 'agreement index', which identifies the level of consensus opinion over a given time period (A_t^i) as:

$$A_t^i = 1 - \sqrt{1 - (B_t^i)^2} \tag{2}$$

Cookson and Niessner (2020) recently use a similar agreement index to find significant relationships between abnormal trade volume and changes in disagreement. It is therefore curious as to whether similar trends extend to cryptocurrency markets.

3.2. Performance Metrics

Most cryptocurrency exchanges, including the one analysed in this study, allow individuals to deposit into and withdraw from their account both fiat and cryptocurrencies. Traders can thus deposit one asset, exchange it for another, and then withdraw the funds without having to trade back into the primary asset. Consequently, the notion of a 'round-trip' trade is not a requirement for traders to withdraw their funds, as is the case with traditional brokerage accounts where one can only withdraw funds in the base currency of the broker. The lack of a unified reference currency across cryptocurrency accounts makes performance appraisal equivocal (Gemayel and Preda, 2021).

For example, consider Trader A and who deposits 5,000 US Dollars (USD) and Trader B who deposits one unit of Bitcoin (BTC) at time t when the exchange rate BTC/USD equals 5,000. This suggests that the two accounts are of equal value regardless of whether we value the balances in terms of USD or BTC. Assume that the BTC/USD exchange rate at time $t+1$ has shifted to 6,000. If we value the two balances in USD, this would imply that Trader

A experienced no change in their balance value, while Trader B experienced a 20% unrealised gain. Alternatively, if we valued the two balances in terms of BTC, Trader A would report an unrealised loss of -16.67%, while Trader B would report no change. Thus, by simply changing the valuation reference currency, we obtain different conclusions with respect to the total returns of the two traders, despite neither trader executing any trades. Consequently, to assess the value arising from trading decisions, one must look at the change in the number of units of each asset in a trader's account rather than the change in total value, which may simply be driven by asset price movements relative to the reference currency. For instance, if Trader B sells their BTC for 6,000 at time $t+1$, and subsequently the price drops back to BTC/USD 5,000 and Trader B buys back 1.2 units of BTC, then the trader has realised a gain of 20% on their initial investment.

In the spirit of Gemayel and Preda (2021), we use a profit decomposition approach where total profit is segregated into two main components. The realised profit component captures an individual's profitability related to trading decisions that change the number of units of an asset, while the unrealised or paper profit component captures the passive change in value of an asset relative to a reference currency. To express this mathematically, we denote by $i = 1, \ldots, I$ the unique identifier for each asset, $j = 1, \ldots, J$ the unique identifier for each trader, and t the time at which a valuation is made for all assets. Let $Q^t_{i,j}$ represent the unit quantity of each asset for each trader, $ND^t_{i,j}$ represent the net deposit in units for each asset, and $P^t_{i,ref}$ be the vector of prices of every asset against the reference currency. It follows that the value of an individual's balance for an asset i at time t is given by $P^t_{i,ref} \times Q^t_{i,j}$. Moreover, the value of a trader's balance at time t can be derived by taking the value from the previous consecutive period, adding any net appreciation due to changes in prices, adding any net increase in the number of units of an asset resulting from trading activities valued at time t prices, and adding any net deposits valued using the prices at time t. Extending this formulation to multiple assets, we obtain

$$\begin{aligned} P^t_{i,ref} \times Q^t_{i,j} =& P^{t-1}_{i,ref} \times Q^{t-1}_{i,j} + (P^t_{i,ref} - P^{t-1}_{i,ref}) \times Q^{t-1}_{i,j} \\ &+ (Q^t_{i,j} - Q^{t-1}_{i,j}) \times P^t_{i,ref} + ND^{t-1}_{i,j} \times P^t_{i,ref}. \end{aligned} \tag{3}$$

To calculate the total profit, which is the change in value between two consecutive balances adjusted for net deposits, we move the terms $P^{t-1}_{i,ref} \times Q^{t-1}_{i,j}$ and $ND^{t-1}_{i,j} \times P^t_{i,ref}$ to the left side of the equation, resulting in

$$Total\,Profit^t_{i,j} = \underbrace{(P^t_{i,ref} - P^{t-1}_{i,ref}) \times Q^{t-1}_{i,j}}_{\text{Paper Profit}} + \underbrace{(Q^t_{i,j} - Q^{t-1}_{i,j}) \times P^t_{i,ref}}_{\text{Realised Profit}} \tag{4}$$

The term $(P^t_{i,ref} - P^{t-1}_{i,ref}) \times Q^{t-1}_{i,j}$ represents the paper or unrealised change in value of previously held positions, while $(Q^t_{i,j} - Q^{t-1}_{i,j}) \times P^t_{i,ref}$ captures the realised profits due to active trading, which results in changes in the number of units of an asset not related to deposits or withdrawals. These profit components are summed across all assets in an account to obtain a complete assessment of the trader's performance. One can standardise the profit measures by dividing them by the starting balance of each trading period to obtain return on investment (ROI) metrics. The ROI measures the direction and magnitude of trader performance, which may be affected by extreme values. Thus, we also calculate the success ratio (SR), which takes a value of one if the respective ROI metric at time t is strictly positive, and zero otherwise. A high SR means that a trader has the ability to consistently predict the direction of the market. In this study, we focus on the ROI and SR metrics that pertain to the realised component of profits since we aim to study the impact of sentiment on actual trading decisions.

When dealing with panel data, one must account for potential survivorship bias. For instance, traders who survive due to superior trading performance may be likely to deposit more funds to capitalise on their skill. If we are testing whether positive market sentiment impacts the likelihood of future deposits, then we may conclude that this relation is significant if the surviving traders happen to deposit more funds during a period of positive market sentiment, when in reality they were depositing more funds simply due to the fact that they survived. To address this issue, we adopt the two-step Heckman (1976) procedure, where we first fit a selection equation to capture the probability of trader survival, given by the inverse Mills' ratio (λ), which is then included in the second-step regression model of interest to account for selection bias. This can be generally expressed as:

$$y_{j,t} = \alpha_j + x'_{j,t}\beta + \rho_1 I(t=1)\lambda_1 + \ldots + \rho_T I(t=T)\lambda_T + \epsilon_{j,t}. \tag{5}$$

where $y_{j,t}$ and $x'_{j,t}$ represent the dependent and independent variables of interest given the hypothesis being tested, $\lambda_1, \ldots, \lambda_T$ are the inverse Mills' ratios from the selection models for periods 1 to T, and $I(t = T)$ equals one in period t and zero otherwise. The Heckman correction model allows us to generate unbiased coefficient estimates.

4. Data

4.1. Sentiment Data

Our bullishness index is calculated at weekly intervals using a data set of 1,198,027 individual submissions posted to the Reddit platform between May 19, 2016 and January 5, 2019. All submissions used in this study were posted in one of 32 unique subreddits relating to 19 different cryptocurrencies (as well as a general cryptocurrency subreddit). Figure

1 shows the distribution of submissions posted in cryptocurrency subreddits throughout the observation period. For illustrative purposes, the weekly price of Bitcoin (BTC) is plotted on a secondary axis, expressed in USD. Weekly posting activity across the various cryptocurrency subreddits varies considerably over time: the mean weekly submission volume is 8,613 (median = 8,471) with a standard deviation of 7,389 over the sample period.

Posting activity initially remains stable throughout 2016, with the weekly submission volume ranging from 1,208 to 3,478 and averaging 1,680. However, the average number of submissions published within crypto subreddits in 2017 grew considerably, to 8,541. Figure 1 illustrates that this increase is highly consistent with the general upwards trend in the price of the largest cryptocurrency, BTC, over the same period. The level of submission activity grows consistently over the year, from 1,909 in the first week of January to 35,717 in the penultimate week in December. Shortly afterwards, the most active date for submissions (January 4, 2018) coincides with record high prices observed for a number of cryptocurrencies prior to the "cryptocurrency crash" that commenced on January 6, 2018. Although the mean weekly number of submissions increased in 2018 (12,952), a majority of this posting activity (62.1%) occurred in the first half of the year, at which point subreddit activity declined.

The average level of Reddit sentiment, proxied using our "bullishness" index measure that takes a value between 1 (positive) and -1 (negative), was slightly positive in nature (mean = 0.050, median = 0.050) with a high of 0.118 (observed during November 2018) and a low of -0.012 (observed during August 2016). The bullish nature of the Reddit community is perhaps expected given that: (i) message board platforms are typically bullish in nature (Zhang and Swanson, 2010; Tumarkin et al., 2002), (ii) users are more likely to discuss securities that they already own (Zhang, 2014), and (iii) few individual investors, if any, can short a stock at scale. The average level of community bullishness increases annually over the sample period, from 0.044 in 2016 to 0.046 in 2017 and 0.058 in 2018.

The average number of *ThumbsUp* awarded to a submission (measured at weekly intervals) is 16.91 (median = 16.08) with a standard deviation of 4.13. Interestingly, submissions attracted more *ThumbsUp* shortly after (and to a lesser extent before) cryptocurrencies reached their peak in January 2018, with the maximum weekly average (28.67) observed on the week of January 22, 2018. Comparatively, the lowest weekly average *ThumbsUp* (10.77) occurred at the beginning of August 2016, during a time when crypto price movements were relatively muted. The positive sentiment conveyed within submissions, and the high number of *ThumbsUp* awarded to submissions during a period in which cryptocurrencies prices decreased, may suggest a presence of confirmation bias. Specifically, members of the online community may reward those submission authors expressing a desire to hold in the face of selling pressure. However, it may instead indicate a wider and more active audience base during a time when cryptocurrencies had entered public discourse and were widely discussed in news media.

4.2. Exchange Data

We use transaction-level as well as demographics data of traders from an anonymous cryptocurrency exchange, which we call *BitEx*. A non-disclosure agreement does not allow us to use the name of the exchange; however, we can disclose that the exchange used in this paper was ranked consistently among the top 50 exchanges by volume on CoinMarketCap[7] over the period of study, thus offering readers a better sense of the popularity and reputation of the exchange.

Individuals begin by depositing funds into their account either in cryptocurrencies (through

[7]See `https://coinmarketcap.com/rankings/exchanges/`.

blockchain transactions), or in fiat (via bank transfers). Traders can then start trading the assets listed on the exchange in spot markets. Over the sample period, BitEx allowed long-only trading (i.e. no short-selling), as was typical among cryptocurrency exchanges at the time. After a trader decides they no longer wish to participate in the market, they can either keep their funds in their account, or withdraw their funds in their desired crypto or fiat currency.

The data includes over two million transactions executed by more than 20,000 traders spread across 150 countries from 2016 to 2019. BitEx listed assets over time, and as of the ending date in the data set, the exchange offered 119 assets and 288 direct markets. BitEx records the details of every transaction, including the price, volume, direction, and timestamp, as well as demographics data of each trader, such as age and country of registration, which are based on official documents provided upon registration. This makes such information more reliable compared to when it is self-reported. Nonetheless, we underscore that the physical location of the trader may not be the same as the country of registration since the individual might have relocated during the period analysed, or used verification documents that do not reflect their actual location. Thus, the country variable used in our analyses more loosely controls for the ties a trader has to the country of registration.

We present some descriptive statistics in Table 1. The age of traders on BitEx ranges between 18 to 70 years, with a mean of around 35 years. Regarding account activity, the number of trades executed ranges from 1 to over 70,000, with a mean and median of 97 and 22 respectively. This suggests that many individuals are not intra-day traders and tend to execute no more than one trade per day. There are however some accounts belonging to high-frequency traders, market makers, and arbitrageurs, which exhibit multiple trades per day. Three-quarters of traders trade in at most four different assets, meaning that they are focused on a few investments within the entire set of available assets. As for trade volume, we calculate mean and median values denominated in USD of 422 and 184, respectively. Nonetheless, there were a few very large trades, up to a value of approximately half a million USD, that were executed during the peak of the market in December 2017. Regarding cryptocurrency fund flows in and out of an account, traders deposit on average four times with a mean deposit value of around USD 3,000 and withdraw around seven times with a mean withdrawal value of USD 2,000. These numbers are contrasted to fiat fund flows, where individuals deposit around five times with a mean deposit value of around USD 1,800, and withdraw around three times with a mean value of USD 7,155 per withdrawal.

Regarding the computed ROI metrics, we report mean and median total returns of 1.19% and 1.40%, respectively, and mean and median realised returns of −1.1% and −0.6%, respectively. These figures suggest that, while traders exhibited positive weekly total returns, which may be attributed to the bull market of 2017, they tend to lose money due to active trading.

5. Results

We investigate whether market sentiment (measured using our Reddit "bullishness" index) has any impact on traders' performance, position exposure, as well as fund flows into and out of their trading account. We apply panel regression models including control variables that quantify the overall contemporary and one-period lagged bullishness sentiment of the cryptocurrency market ($Bullishness$), one-period change in bullishness ($\Delta Bullishness$), contemporary and one-period lagged level of agreement ($Agreement$), one-period change in the level of agreement ($\Delta Agreement$), natural logarithm of the number of subreddit subscribers ($Subscribers$), as well as the average number of submission thumbs-up given by subscribers ($ThumbsUp$). We also include trader-specific parameters that are calculated on a cumulative rolling basis up to but not including time t, such as a trader's past trading performance (ROI_{Career} and SR_{Career})[8], cumulative number of trades ($Trades$), the count of unique assets traded ($Assets$), the average trade size ($Size$), the mean balance ($Balance$), and the volatility of the cryptocurrency market ($Volatility$), which is proxied by the standard deviation of hourly returns of BTC/USD over a one week window.[9]

Moreover, we control for demographics including country of residence — which we do not report due to spatial limitations and lack of any distinct geographical significance — and age (Age).[10] We account for potential non-linearity between age and performance as individuals become more risk-averse as they mature. All models are augmented with asset and trader fixed-effects. We use USD as the reference currency to calculate returns. Since the majority of traders in our sample are not intra-day traders, and in keeping with the frequency of our sentiment measure, we calculate returns using a weekly sampling frequency. Finally, as mentioned in Section 3, we control for the potential of survivorship bias by adopting the Heckman (1976) procedure in our analyses. While we find significant estimates for some of the ρ variables in model 5, suggesting the presence of survivorship bias, the effect and significance of the coefficients of the covariates of interest are very similar to those found

[8]Due to the high correlation between ROI_{Career} and SR_{Career}, we do not include both variables together in the models. Moreover, the career parameters are calculated on a cumulative rolling basis, in order to get a complete picture of a trader's performance and skill.

[9]In the spirit of Vidal-Tomás et al. (2019), we conduct robustness checks for this proxy measure by constructing indices using different numbers of constituents and weightings (including equal weights); however, the conclusions are similar given that the largest three cryptocurrencies (Bitcoin, Ethereum, and Ripple) constituted around 70% of the index over the period of study, and the indices were highly correlated with the price of Bitcoin. For the remainder of this study, we therefore proceed with our original proxy measure stated in the main text; however, we caution future research that Bitcoin's dominance in the crypto market may change.

[10]As traders' gender information was not provided to us by *BitEx*, we are unable to control for this in the current study. In future research, it may prove useful to establish the extent to which traders' gender may influence performance and behaviour.

when we conducted the analyses without applying the Heckman procedure. As such, the presence of survivorship bias in our sample does not affect the inferences from our results, thus we only report the results of the second-step models due to spatial limitations.

5.1. Sentiment and Performance

Our first analysis examines the impact of market sentiment on trader performance, and results are presented in Table 2. Model (1.a) is linear and uses $ROI_{Realised}$ as the dependent variable. The results show that when the contemporaneous level of bullishness is high, traders tend to realise positive returns, which may be considered as a signal to the traders by the market to realise the gains on their investments. The lagged bullishness parameter is not statistically significant, which means that past market sentiment does not impact current trading decisions. Moreover, a positive weekly change in the degree of bullishness also leads to a positive and significant effect on realised returns, which suggests that traders are sensitive not only to the prevalent level of market sentiment, but also to variations that may indicate potential price changes. With respect to the degree of agreement across submissions, we find a significant inverse effect only at the 90% confidence level, implying that traders do not benefit from information contained in submissions that are similar in nature or sentiment. The lagged agreement coefficient is not statistically significant; nevertheless, we find that a positive change in the degree of agreement, $\Delta Agreement$, leads to a positive effect on trading performance, suggesting that traders receive a valuable signal from the market when the overall sentiment converges to a consensus. Our results show that the greater the number of subscribers to a post, the lower the traders' returns, which may be an indication of excessive noise in market sentiment, leading to a distorted view of market direction. As for our reputation measure *ThumbsUp*, we find no statistically significant evidence that author credibility plays a role in traders' performance.

We find a negative coefficient for ROI_{Career}, which suggests a reversion towards the mean whereby traders with historically low (high) returns are likely to exhibit high (low) returns in the future. This may be, to some extent, due to the high degree of ambiguity governing the cryptocurrency market. The negative coefficient for the $Trades$ parameter suggests that excessive trading is detrimental to performance, as is commonly documented in financial literature. We find that individuals who trade in multiple assets have a slight advantage over those who trade fewer assets as indicated by the positive coefficient of the $Assets$ parameter. This implies that diversification brings with it a wider scope of trading opportunities. Moreover, we find positive coefficients for $Size$ and $Balance$, which suggest that traders who execute larger trades and have larger balances are likely to realise higher returns.[11]. Volatility has a negative impact on trading performance, implying that traders execute sub-optimal trades in times of heightened market uncertainty. Regarding the age of traders, the results show a concave relation, whereby performance is higher for individuals who are in the middle of the age spectrum. One explanation for this is that these traders are more familiar with the concept of cryptocurrencies compared to their older counterparts thus making them more prone to take on excess risk, in addition, they are more experienced and have more capital to invest relative to their younger counterparts allowing them to participate in potentially profitable trades. We highlight that the concept of cryptocurrencies is relatively new to traders of all ages. As such, we use age as a general proxy for financial maturity rather than specific knowledge of the crypto field.

In unreported results due to spatial limitations, we run Model (1.a) on sub-period samples prior to, and post January 1, 2018, which represent strong bullish and bearish markets,

[11]These variables may be considered as proxies for trader sophistication, such that those with greater wealth are able to access more advanced trading and risk management tools that can offer a competitive advantage.

respectively. We find that the parameter for contemporary bullishness is only positive and significant within the bull-market sample, implying that when market bullishness is high during an upward trending market, this translates into positive realised returns more so than when the overall market is trending down. Hence, realising profits when the market is trending up will more likely result in a total positive return compared to doing the same in a downtrend. We find that the effect of $\Delta Bullishness$ is around six times larger in the bull market relative to the bear market, suggesting that traders are more sensitive to changes in sentiment during positive market states.

With respect to the degree of agreement, we find that this parameter is largely significant and negative in the bear market sample. This may be due to traders agreeing on the fact that the market peak has already been reached in hindsight (i.e. greater agreement that the market is governed by a bearish trend), thus resulting in larger negative returns. Moreover, we find only for the bear market sample that a positive change in the degree of agreement, $\Delta Agreement$ leads to a positive effect on trading performance. Hence, while agreement on the fact that a market is in a downtrend implies lower realised returns, the greater degree of consensus — in itself — is valuable information to traders as they may decide to realise their returns given the state of the market. Regarding the number of subscribers, we report a negative and significant coefficient only for the bear market sample. This may imply a form of herding effect that is only prevalent during times of market distress, such that the larger the number of people viewing a post during a downtrend, the greater the degree of panic, consequently leading to larger negative returns. As for the $ThumbsUp$ parameter, we find a positive effect for the bear market sub-sample, indicating that author credibility plays a significant positive role in terms of performance during times of market distress.

While Model (1.a) allows us to measure the effect of market sentiment on the magnitude of a *trade* decision, it does not allow us to consider the times when traders choose to not participate in the market. In other words, while the ROI of a trader captures performance related to actual trades, it fails to consider the scenarios where a trader chooses not to trade. Gemayel and Preda (2021) argue that the outcome of a trader's decision, labelled as $Trade_D$, may be classified into three mutually exclusive states: 1) trade and win, 2) trade and lose, and 3) not trade. These states do not fall on an ordinal scale since a decision to *trade*, regardless of whether the outcome is a win or a loss, cannot be compared to a decision to *not trade*. Thus, the outcome of a trader's decision is defined as a multinomial variable, which takes the value of zero (i.e. baseline response) if the trader decides not to trade, one if the trade results in a win, and two if the trade results in a loss. We fit Model (1.b), where the odds of a win or a loss are measured against the baseline response. This results in two binary logistic models of the odds of a winning trade, and odds of a losing one, relative to a no-trade decision (labelled as "Gain" and "Loss" respectively). These models are fitted simultaneously so that the intercepts and coefficients of the other odds equal the differences of the corresponding intercepts and coefficients.

We find that higher levels of bullishness, both contemporary and lagged, decrease the odds of a losing trade and increase the odds of a winning one relative to a no-trade decision. We highlight that the effect of contemporary bullishness is around twenty times that of the lagged parameter, which may imply that traders react more strongly to market sentiment at the time of their trading decision. This result echoes the finding from Model (1.a) and may be explained by a combination of the exchange offering long-only services over the sample period of investigation, and a general predisposition among traders to buy cryptocurrencies, resulting in a higher (lower) propensity to execute a winning (losing) trade. Regarding $\Delta Bullishness$, we find that a positive change in bullishness leads to a higher likelihood of executing *both* winning and losing trades. One explanation for this is that some traders follow momentum-based strategies, while others adopt contrarian strategies. As such, momentum (contrarian) traders will gain (lose) when the market is bullish — given that the exchange offered long-only trading services. When the level of agreement is high, traders tend to execute fewer trades (both winning and losing ones) relative to a no-trade decision. This suggests that consensus around market sentiment decreases the likelihood of active trading, while a lower level of agreement motivates traders to seek trading opportunities. A similar yet much smaller effect is reported for the lagged agreement parameter for both Loss and Gain models, which potentially implies that traders react more strongly to contemporary levels of agreement when making a trading decision. Similarly, a positive change in agreement decreases the likelihood of active trading; however, to a lesser extent compared to the level of agreement. We find that a higher number of $Subscribers$ leads to a lower likelihood of both losing and winning trades, which supports our earlier argument that excessive noise in market sentiment decreases the general propensity towards active trading. Further, $ThumbsUp$ is found to have a positive effect on the likelihood of both winning and losing trades. Combining this finding with our argument that individuals may be categorised as momentum or contrarian traders, it follows that a high number of thumbs-up for a bullish post may be perceived as confirmation of the sentiment of the market, which consequently increases the likelihood of a win (loss) for the momentum (contrarian) traders.

Traders who have a high success ratio over their trading career are less likely to execute a losing trade and more likely to execute a winning trade in the future relative to a no-trade decision, as indicated by the coefficients of the SR_{Career} variable. Consequently, those who had the ability to correctly predict the direction (but not necessarily the magnitude) of price movements in the past, have a higher likelihood to do so in the future. Such a pattern is indicative of persistence in predictive ability. The coefficients for the $Trades$ parameter show that the more frequent individuals trade, the higher (lower) the likelihood that they will execute a losing (winning) trade, which echoes the argument that excessive trading is detrimental to performance. We report positive coefficients for the $Assets$ variable for both models, which implies that a wider set of investments results in a higher likelihood of executing both winning and losing trades. With respect to $Size$ and $Balance$, we report positive coefficients for both models, which means that individuals with larger average position sizes and wealth are more likely to execute both winning and losing trades. In other words, these individuals have more funds to invest, which is manifested in larger position sizes, and a higher propensity to trade rather than sitting on the sidelines. Higher levels of market volatility increase the probability of both losing and winning trades, since traders are enticed to try and capture potentially profitable trades instead of missing out by not participating in the market. Finally, we find that more mature traders are more likely to execute a winning trade and less likely to execute a losing one. Nonetheless, this relation is non-linear as suggested by the coefficients of the Age^2 parameter, which may be due to the older traders being less familiar with the cryptocurrency space, thus putting a slight downward bias on their performance.

5.2. Sentiment and Trade Exposure

Market sentiment may not only have an impact on a trader's decision to buy, sell, or opt out of trading, but also on how much to invest in each trade. We examine how traders alter their exposure on future trades based on the overall market sentiment. To do so, we run two models; Model (2.a) is linear and uses the natural logarithm of the trade size at time t as the dependent variable, while Model (2.b) is logistic and uses a binary dependent variable that takes the value of one if the trade size at time t is larger than the trader's career average trade size, and zero otherwise. The results are presented in Table 3.

For both models, we find negative and statistically significant coefficients for $Bullishness$, and statistically insignificant coefficients for the lagged parameter, which suggests that when contemporary market sentiment is very bullish, traders are likely to execute smaller trades — in both absolute dollar terms, as well as in relation to their career average. Therefore, traders become more cautious and stake smaller amounts when contemporary market sentiment is highly optimistic. Nevertheless, a positive change in bullishness, captured by $\Delta Bullishness$, has a positive impact on trade size. This suggests that, while traders are cautious with respect to high levels of bullishness, they do increase their trade exposure where a positive change in sentiment is observed. Although the levels of contemporary and lagged online agreement are not found to have any significant effect on trade size, a positive change in agreement does have a positive impact on trade size, indicating that a shift towards consensus around market sentiment drives traders to invest larger amounts. Trade size is also found to increase with the number of $Subscribers$, which may be perceived by traders as confirmation of the market sentiment embedded in the submissions. However, a higher number of subscribers does not lead traders to increase their trade size to an amount that is higher than their historical average. Thus, the information traders infer from a higher number of subscribers, while it increases the size of a trade in absolute terms, is not sufficient to entice traders to deviate in excess of their norm. We report positive coefficients for $ThumbsUp$ in the case of both models, which suggests that this social signal is perceived by traders as confirmation of the prevalent market sentiment. As such, traders are more likely to increase their trade size in both absolute terms as well as in relation to their own career average.

For both models, we find negative coefficients for ROI_{Career}, suggesting that individuals who have historically low returns are likely to increase the size of their future trade. This behaviour can be equated to a martingale betting system whereby traders exhibit the gambler's fallacy, such that they increase their exposure on future trades, with the belief that their subsequent prediction will be correct and will compensate for their poor past performance. We find that the more traders trade, the larger the size of their subsequent trade. Again, this may be a manifestation of the martingale betting system where traders keep increasing their trade size the more they trade, thus altering their risk appetite. A wider trading set results in smaller sized trades, as indicated by the negative coefficients of the *Assets* parameter. This may be due, to some extent, to traders allocating smaller amounts of their limited funds to a larger number of investments. With respect to *Size*, we find no statistical significance; however, we do report positive coefficients for the *Balance* parameter. Thus, individuals with larger balances tend to increase their exposure on future trades due to the availability of capital at their disposal. Market volatility also leads to an increase in trade size as traders try to capture potentially profitable opportunities. As for the age of a trader, we find a concave relation such that those who fall in the middle of the age spectrum are likely to have larger trade sizes. This can be explained by a higher level of wealth relative to their younger counterparts, and more tolerance for risk compared to older traders.

5.3. Sentiment and Decision to Deposit

In this section, we investigate whether market sentiment drives traders to deposit additional funds into their account. To do so, we run three models; Model (3.a) is linear and uses the natural logarithm of the amount deposited (in USD) as the dependent variable, Model (3.b) is logistic and uses a binary variable that takes the value of one if the trader makes a deposit, and zero otherwise. Model (3.c) is the Andersen-Gill (AG) counting process model, which is a generalised form of the Cox model where the variable of interest is the time since entry of the trader into the sample until a deposit event occurs. In contrast to the Cox proportional hazards model, which only considers time until the occurrence of the first event, the AG model accounts for the hazard rate of multiple events, and builds on the assumption that the time increments between events for a certain subject are conditionally uncorrelated given the covariates. In addition to the previously-mentioned control variables, we include the $Fiat$ parameter, which takes the value of one if the deposit is made in fiat, and zero if it is made in crypto. Table 4 presents the results.

We find that the contemporary level of bullishness has: (i) a negative effect on the size of deposits; (ii) a positive effect on the likelihood of a deposit occurring; and (iii) decreases the time interval between two consecutive deposits (i.e. increase in the hazard rate). This implies that when the market is very bullish, traders are likely to deposit more, but in smaller amounts, yet at a much faster rate to capitalise on the state of the market. The lagged level of bullishness has no significant impact on deposits. A positive change in bullishness — while it has no significant effect on the size of the deposits — increases the likelihood of traders depositing additional funds and increases the rate at which a deposit is likely to occur. We find that a higher contemporary level of agreement in sentiment leads to larger deposits, a higher probability of a deposit occurring, and an increase in the frequency of deposits. Thus, a higher degree of market consensus attracts additional funds into the cryptocurrency market. The same relations are also reported for the $\Delta Agreement$ parameter, except that the magnitude of the coefficients are much smaller. Nevertheless, any change towards a higher degree of consensus about market sentiment increases deposits in terms of amount, likelihood, and frequency.

We find that $Subscribers$ has a negative impact on the size of deposits, and decreases the hazard rate of future deposits (i.e. makes the time interval longer). This suggests that more subscribers may be an indication of greater noise around market sentiment, thus dampening future deposits. We report positive coefficients for the variable $ThumbsUp$ across all models, which suggests that such positive social reinforcement increases the size and likelihood of deposits, and increases the hazard rate of future deposits, as traders act quickly to capitalise on market sentiment. Regarding $Fiat$, we find that fiat deposits are generally larger than cryptocurrency deposits (valued in USD), which is an indication of money flowing into the cryptocurrency space. Nevertheless, the coefficient in Model (3.b) is negative, implying a lower likelihood of a fiat deposit relative to one made in cryptocurrencies. This can be explained by the lengthy and expensive fund transfer services offered by banks in comparison to blockchain technology. This also explains the lower hazard rate (longer time) for fiat deposits, given by the negative coefficient of $Fiat$ in Model (3.c).

An inverse relation is identified between ROI_{Career} and both the size and likelihood of deposits, meaning that those who performed poorly in the past are more likely to deposit larger amounts in the future to keep participating in the market. Furthermore, ROI_{Career} has a positive effect on the hazard rate of future deposits, which implies that those who have performed well in the past attribute this success to their own superior trading abilities, and thus try to capitalise on their skill through faster deposits. Regarding the $Trades$ parameter, we find that the more individuals trade, the larger the size, the higher the likelihood, and the faster the frequency of their deposits. This implies that the more traders participate in the cryptocurrency market, the more they become attracted to it, thus increasing the proportion of their wealth invested in this asset class. With respect to $Assets$, we find that the wider the investment set of a trader, the larger, the more likely, and the faster they will deposit. This finding is unsurprising since those who invest in multiple assets require more funds in general. We do not find any significant effect for $Size$ across all models. Nonetheless, we report positive coefficients for the $Balance$ parameter, suggesting that those with larger balances are more likely to deposit in larger amounts and more frequently, as these individuals may have excess wealth that they would want to invest in the cryptocurrency market. Market volatility has a positive effect on the size, likelihood, and frequency of deposits, which may be due to traders wishing to transfer capital into the crypto market in order to take advantage of potentially profitable opportunities arising from heightened uncertainty. Regarding the age of traders, we find a concave relation whereby those in the middle of the age spectrum are more likely to deposit larger amounts due to their higher level of disposable income and willingness to take risks. Nonetheless, the results also show that more mature traders deposit at a slower rate, which may be an indication that they take their time before allocating additional capital to this novel asset class.

5.4. Sentiment and Decision to Quit

In the final analysis, we investigate whether market sentiment impacts traders' decisions to withdraw their funds. Similar to the previous analysis, we run three models; Model (4.a) is linear and uses the natural logarithm of the amount withdrawn (in USD) as the dependent variable, Model (4.b) is logistic and uses a binary variable that takes the value of one if the trader makes a withdrawal, and zero otherwise, and Model (4.c) is the AG model which uses the time since entry of the trader into the sample until a withdrawal event occurs as the outcome variable. Table 5 presents the results.

We find no statistical significance for the *Bullishness* parameter for Model (4.a), which means that the level of market bullishness does not affect the size of withdrawals. However, the contemporary level of bullishness is found to have a positive effect on the likelihood of a withdrawal and increases the hazard rate of a withdrawal event occurring. This may be due to traders withdrawing their profits quickly after the market has performed well. We report no significant effect for the lagged bullishness parameter, which suggests that the decision to exit the market is driven by the current market sentiment. When we look at the change in the degree of bullishness, we only find a significant positive impact on the likelihood of withdrawal, which supports our earlier argument that a bullish trend entices traders to withdraw some of their profits. For the *Agreement* variable, we find no significant effect on the amount withdrawn; however, we report a negative coefficient in Model (4.b) suggesting that a higher level of agreement among submissions leads to a lower likelihood of a withdrawal occurring. Hence, the reduced level of uncertainty around market sentiment encourages traders to keep their funds invested in the crypto market. Moreover, *Agreement* has a negative impact on the hazard rate, which also supports the notion that reduced uncertainty about market sentiment increases the time interval between withdrawals. We find no significant effect for the lagged agreement parameter.

Similar results are found for $\Delta Agreement$, whereby a positive change in agreement leads to a lower likelihood of a withdrawal occurring as well as a higher time interval between withdrawals. Again, this is attributed to traders remaining in the market when there is a shift towards consensus about sentiment. We only find a positive and statistically significant coefficient for the *Subscribers* parameter in Model (4.a), which implies that an increase in the number of subscribers may be perceived to be a signal of an overcrowded market, thus prompting larger withdrawals. Curiously, coefficients for the *ThumbsUp* variable across all models are positive, suggesting that a higher degree of social reinforcement manifested through this feature leads to larger, more likely, and more frequent withdrawals. Given that *ThumbsUp* were awarded more frequently in the early weeks of 2018, at a time during which cryptocurrency prices fell considerably, it may be the case that users may award those maintaining positions while cautiously withdrawing a proportion of their own holding.

We find that fiat withdrawals are generally larger in size, less likely to occur, and less frequent than those made in cryptocurrencies. This can be explained by the fact that blockchain technology allows traders to withdraw smaller amounts, at lower costs, and at a much quicker rate compared to traditional banking services. We report an inverse relation between ROI_{Career} and the size, likelihood, and hazard rate of a withdrawal. Hence, the higher the trader's past performance, the smaller the amount and the less likely they are to withdraw their funds, given the good returns they have experienced in the past. Individuals who trade excessively are likely to withdraw smaller amounts and in a less frequent fashion, as the funds would be invested in their strategies and investments. Moreover, we find that the wider the investment set of a trader, the larger and the more likely the withdrawal, which may be due to the out-performance of some investments that provide the trader with excess wealth that can be withdrawn.

We do not find any significant effect for trade size across all models, but we do find that the larger a trader's balance, the larger the withdrawn amount and the more likely a withdrawal is to occur, which is plausible given the higher amount of funds available in their account. We also report that the time interval between withdrawals is longer for larger balances, which may be due to a higher level of wealth among these traders who may not be in a hurry to cash out. With respect to volatility, we find a negative impact on the amount, likelihood, as well as the hazard rate of a withdrawal, indicating that individuals would rather keep their funds available for trading during times of heightened uncertainty. Finally, our results show that middle-aged traders have the largest withdrawal sizes and are more likely to withdraw, which can be explained by the relatively larger deposits made previously due to their higher disposable income. However, these traders also have slower withdrawal rates, indicating that they have the capacity to extend their search for profitable investments, as they are less reliant on their cryptocurrency funds due to their higher income level.

6. Conclusion

"Financial markets live on gossip" (Mainelli, 2003, p. 629), with previous evidence suggesting that sentiment detected within online discussion and news media has the ability to influence financial markets (Nardo et al., 2016; Kearney and Liu, 2014; Zhang, 2014). Sentiment-induced buying and selling is an important role in the valuation of financial assets (Chau et al., 2016) and in this paper we hypothesise that the role of sentiment is more pronounced in the market for cryptocurrencies, as it represents: (i) an ambiguous market with little historical precedent on which to inform trader decisions; and (ii) a market defined by a lack of quantifiable fundamental information on which to base crypto-asset valuations (Gurdgiev and O'Loughlin, 2020). Thus, cryptocurrencies have value today because of public excitement (Shiller, 2020).

Whereas much emphasis has previously been placed on behaviour at the aggregate market level, comparatively little focus has been placed on the decision-making process of individual traders. Therefore, we use a data set of over two million transactions executed on a cryptocurrency exchange to test whether sentiment conveyed within cryptocurrency communities on Reddit impacts upon the performance, position exposure, as well as deposit and withdrawal behaviour of cryptocurrency traders. Our evidence supports the notion that sentiment plays a role in the investment decision-making process. For example, traders are found to realise positive returns when sentiment is particularly bullish towards cryptocurrencies, and performance is found to respond to positive changes in online sentiment. Thus, our evidence is consistent with the prior findings of associations between sentiment and cryptocurrency returns (Guégan and Renault, 2020; Valencia et al., 2019; Abraham et al., 2018). However, evidence suggesting that increased community bullishness one week influences traders' activity in the following week is comparatively weaker, with a lack of significant results when analysing lagged, as opposed to contemporaneous, sentiment variables.

Positive changes in the level of Reddit bullishness lead to traders executing larger trades, and there is a higher probability of depositing funds into cryptocurrency exchange accounts during periods of prevalent positive market sentiment. However, such periods of community bullishness concurrently lead to an increased likelihood of withdrawing funds, inferring that while some traders are willing to 'top up' their accounts in response to public excitement, others engage in 'profit taking'. This is supported to some extent by our finding that higher sentiment leads to smaller yet more frequent deposits, as long-term traders look to place less frequent heavy bets during times when market sentiment is lower, and thus when cryptocurrencies are perhaps perceived to be undervalued by the market. However, the level of online sentiment is not found to result in increased withdrawals into fiat currency. Further, relationships are found to be contemporaneous in nature, with few significant results identified in the case of lagged sentiment variables.

Our other sentiment-based measures of agreement, reputation, and audience produce less compelling results. Using the number of subscribers to a cryptocurrency subreddit as a proxy for audience size, we find little evidence that performance is driven by a 'silent majority' of 'side-lined investors' who contribute infrequently (Mai et al., 2018; Cao et al., 2002), or that the reputation of those contributing to the online discussion has pronounced effects on a decision-making process. Further, the evidence suggesting that community consensus (agreement) significantly impacts traders' decision-making is inconsistent, and in some instances contrary to the extant literature (Cookson and Niessner, 2020).

The findings of this study contribute to the burgeoning literature on the role of sentiment in traders' decision-making, and suggest that sentiment does play a significant role in the decision to trade, deposit and withdraw over contemporaneous time periods. However, we must be careful when addressing the causal nature of any relationships identified in this research, as further investigation is needed regarding the direction of information flow between online communities and cryptocurrency markets. Perhaps a key limitation of our analysis is that we build on the assumption that traders on BitEx had exposure to information posted on the Reddit platform, when this may be the case for only some – or indeed, none – of the cryptocurrency traders studied. However, positive associations have been identified between online communities and financial markets in prior literature (Zhang, 2014), and prior research concerning online financial communities suggests that individuals prefer to interact with those holding similar beliefs (Gu et al., 2014). It is therefore reasonable to suggest that a number of those discussing cryptocurrencies hold an interest in the underlying assets.

Additionally, the current research does not disaggregate sentiment by individual currencies and addresses cryptocurrency sentiment in a general sense. It may be the case that investors are simultaneously positive towards some currencies and negative towards others. Therefore, future research could employ indices specific to individual cryptocurrencies in order to avoid this potential dilution and better understand the underlying dynamics.

Finally, while it was challenging to obtain data on traders, we encourage researchers to also attempt to conduct similar investigations on more recent data, since the cryptocurrency market has developed significantly over the past few years given the innovations in the decentralised finance (DeFi) space.

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Figure 1: Weekly Cryptocurrency Submissions on Reddit and Bitcoin Price

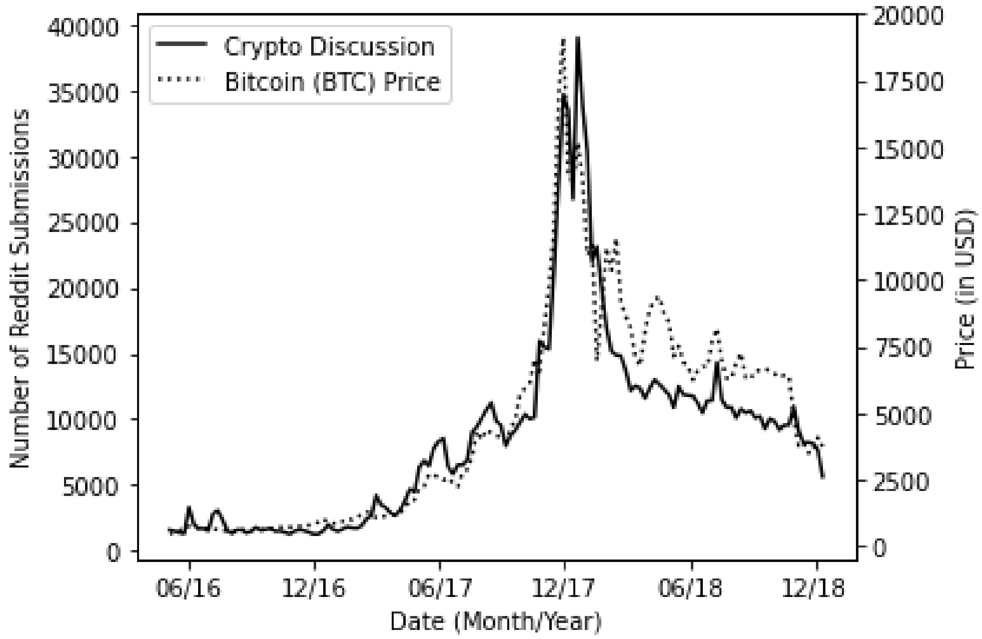

Table 1: **Descriptive Statistics of BitEx from 2016 to 2019.** The following table shows descriptive statistics of traders on BitEx, including the age of the trader, *Trader Age*. *Trades* represents the total number of trades executed, and *Assets* is the number of unique assets traded by each trader. *Trade Size (USD)* is the average trade size executed by a trader denominated in USD. We report the number of crypto and fiat deposits and withdrawals, and the average size of these transactions denominated in USD. Moreover, we present descriptive statistics of weekly return on investment (ROI) metrics including the total return, ROI_{Total}, and the decomposed return components, $ROI_{Realised}$ and ROI_{Paper}.

	Min.	**1st Qu.**	**Median**	**Mean**	**3rd Qu.**	**Max.**
Trader Age (Years)	18	28.87	33.56	35.44	39.84	70
Trades	1	9	22	97	34	70,689
Assets	2	2	3	3.53	4	68
Trade Size (USD)	1	12	184	422	355	573,473
Number of Crypto Deposits	1	1	2	4.48	4	1,120
Crypto Deposit Size (USD)	1	26.04	283	3,024.61	1,544.78	3,260,800
Number of Crypto Withdrawals	1	1	3	6.63	7	2,124
Crypto Withdrawal Size (USD)	1	94.67	410.01	1,977.12	1,265.37	4,785,600
Number of Fiat Deposits	1	1	3	5.04	6	197
Fiat Deposit Size (USD)	50	130	506.35	1,769.82	1,400	3,842,229
Number of Fiat Withdrawals	1	1	1	3.06	3	81
Fiat Withdrawal Size (USD)	70	243.47	1,249.75	7,155.41	5,075.75	3,947,564
ROI_{Total}	-41.32%	-0.03%	1.40%	1.19%	3.38%	40.06%
$ROI_{Realised}$	-14.8%	-2.20%	-0.60%	-1.10%	0.30%	12.60%
ROI_{Paper}	-34.40%	0.0%	1.42%	1.29%	3.43%	40.72%

Table 2: **Sentiment and Performance.** This table shows the results of models examining the impact of sentiment on trader performance. Model (1.a) is linear and uses $ROI_{Realised}$ as the dependent variable, while Model (1.b) is multinomial and uses the nominal $Trade_D$ variable. Independent variables comprise a set of parameters that quantify the sentiment of submissions, including contemporaneous and one-period lagged bullishness levels, $Bullishness$, one-period change in bullishness, $\Delta Bullishness$, contemporaneous and one-period lagged levels of agreement, $Agreement$, one-period change in the level of agreement, $\Delta Agreement$, natural logarithm of the number of subscribers, $Subscribers$, as well as the average number of submission thumbs-up, $ThumbsUp$. Each model is also regressed on a cumulative rolling average of the dependent variable that is calculated up to but not including time t, given by ROI_{Career} and SR_{Career}, for Model (1.a) and Model (1.b), respectively. We include trader-specific control variables such as the cumulative number of trades, $Trades$, count of unique assets traded, $Assets$, average trade size, $Size$, mean balance, $Balance$, and volatility of the cryptocurrency market, $Volatility$, proxied by the standard deviation of hourly returns of BTCUSD over a one week window. We control for country of residence, and age, Age. All models include trader and asset fixed-effects. We report the number of observations, N, the adjusted R^2 for the linear model, and the χ^2 for the multinomial model.

	Model (1.a)			**Model (1.b)**					
				Loss			**Gain**		
	Coef.	**S.E.**		**Coef.**	**S.E.**		**Coef.**	**S.E.**	
$Bullishness_t$	0.006	0.002	***	-1.790	0.001	***	2.364	0.001	***
$Bullishness_{t-1}$	0.0001	0.002		-0.081	0.0001	***	0.121	0.0001	***
$\Delta Bullishness_{t,t-1}$	$4.0e^{-5}$	$1.1e^{-5}$	***	0.193	0.001	***	0.180	0.001	***
$Agreement_t$	-0.057	0.03	*	-4.959	0.002	***	-2.881	0.001	***
$Agreement_{t-1}$	-0.003	0.029		-0.445	0.001	***	-0.345	0.001	***
$\Delta Agreement_{t,t-1}$	$3.4e^{-5}$	$1.2e^{-5}$	***	-0.018	$9.4e^{-4}$	***	-0.001	$-1.0e^{-4}$	***
$Subscribers_t$	$-1.0e^{-4}$	$2.3e^{-5}$	***	-0.096	0.002	***	-0.041	0.001	***
$ThumbsUp_t$	$1.0e^{-5}$	$1.0e^{-5}$		0.338	0.004	***	0.258	0.003	***
$ROI_{Career,t}$	-0.047	0.008	***						
$SR_{Career,t}$				-0.302	$1.0e^{-5}$	***	1.037	$2.1e^{-5}$	***
$Trades_t$	$-4.4e^{-5}$	$1.1e^{-5}$	***	$1.4e^{-4}$	$3.7e^{-5}$	***	$-1.2e^{-4}$	$3.5e^{-5}$	***
$Assets_t$	$2.7e^{-4}$	$1.0e^{-5}$	***	0.066	$9.8e^{-5}$	***	0.075	$1.1e^{-4}$	***
$Size_t$	$4.2e^{-6}$	$1.4e^{-7}$	***	$3.3e^{-5}$	$1.0e^{-5}$	***	$2.7e^{-5}$	$1.0e^{-5}$	***
$Balance_t$	$2.4e^{-5}$	$6.2e^{-6}$	***	$4.2e^{-4}$	$9.0e^{-5}$	***	0.001	$9.4e^{-5}$	***
$Volatility_t$	$-6.1e^{-4}$	$1.0e^{-4}$	***	0.004	$3.0e^{-5}$	***	0.004	$3.1e^{-5}$	***
Age	$8.1e^{-4}$	$9.4e^{-5}$	***	$-1.2e^{-4}$	$3.0e^{-5}$	***	$4.2e^{-4}$	$8.9e^{-6}$	***
Age^2	$-3.5e^{-5}$	$1.1e^{-5}$	***	$1.4e^{-5}$	$2.3e^{-6}$	***	$-1.3e^{-5}$	$3.3e^{-6}$	***
N	250,336			888,398					
$Adj.\ R^2$	28.2%								
χ^2				43.4					

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 3: **Sentiment and Trade Exposure.** This table shows the results of models examining the impact of sentiment on trade exposure adjustment. Model (2.a) is linear, where the dependent variable is the natural logarithm of trade size at time t. Model (2.b) is logistic and uses a binary dependent variable, which takes the value of one if the size of the trade at time t is larger than the historical average, and zero otherwise. Independent variables comprise a set of parameters that quantify the sentiment of submissions, including contemporaneous and one-period lagged bullishness levels, $Bullishness$, one-period change in bullishness, $\Delta Bullishness$, contemporaneous and one-period lagged levels of agreement, $Agreement$, one-period change in the level of agreement, $\Delta Agreement$, natural logarithm of the number of subscribers, $Subscribers$, as well as the average number of submission thumbs-up, $ThumbsUp$. We include trader-specific control variables that are calculated up to but not including time t, such as the cumulative rolling average of a trader's trading performance, ROI_{Career}, cumulative number of trades, $Trades$, count of unique assets traded, $Assets$, average trade size, $Size$, mean balance, $Balance$, the volatility of the cryptocurrency market, $Volatility$, proxied by the standard deviation of hourly returns of BTCUSD over a one week window. We control for country of residence, and age, Age. All models include trader and asset fixed-effects. We report the number of observations, N, the adjusted R^2 for the linear model, and the $Pseudo\ R^2$ for the logistic model.

	Model (2.a)			**Model (2.b)**		
	Coef.	**S.E.**		**Coef.**	**S.E.**	
$Bullishness_t$	-3.789	1.237	***	-3.572	1.156	***
$Bullishness_{t-1}$	-0.117	1.087		-2.507	1.688	
$\Delta Bullishness_{t,t-1}$	0.030	0.011	***	0.041	0.016	***
$Agreement_t$	-3.212	2.414		-3.360	2.358	
$Agreement_{t-1}$	-1.129	0.754		-0.840	0.598	
$\Delta Agreement_{t,t-1}$	0.009	0.004	**	0.015	0.005	***
$Subscribers_t$	0.186	0.022	***	-0.420	0.026	***
$ThumbsUp_t$	0.027	0.010	***	0.038	0.013	***
$ROI_{Career,t}$	-0.148	0.017	***	-0.212	0.016	***
$Trades_t$	$1.0e^{-4}$	$2.4e^{-5}$	***	$1.0e^{-4}$	$3.0e^{-5}$	***
$Assets_t$	-0.023	0.001	***	-0.031	0.001	***
$Size_t$	$-3.0e^{-5}$	$1.2e^{-5}$		$-6.6e^{-4}$	$7.8e^{-4}$	
$Balance_t$	$2.2e^{-4}$	$4.0e^{-5}$	***	$2.4e^{-4}$	$1.6e^{-5}$	***
$Volatility_t$	$3.2e^{-4}$	$1.2e^{-4}$	***	0.001	$2.0e^{-4}$	***
Age	$3.3e^{-4}$	$9.0e^{-5}$	***	$1.0e^{-4}$	$2.0e^{-5}$	***
Age^2	$-2.0e^{-5}$	$3.0e^{-6}$		$-9.3e^{-6}$	$3.2e^{-7}$	***
N	250,336			250,336		
$(Adj.\vert Pseudo)\ R^2$	53.3%			44.9%		

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 4: **Sentiment and Deposits.** This table shows the results of models examining the impact of sentiment on traders' decision to deposit additional funds. Model (3.a) is linear and uses the natural logarithm of the deposited funds at time t valued in USD as the dependent variable. Model (3.b) is logistic and uses a binary dependent variable that takes the value of one if the trader makes a deposit, and zero otherwise. Model (3.c) is the Andersen-Gill (AG) model where the outcome variable is the time since entry into the sample until a deposit has occurred. Independent variables include parameters that quantify the sentiment of submissions, including contemporaneous and one-period lagged bullishness levels, *Bullishness*, one-period change in bullishness, Δ*Bullishness*, contemporaneous and one-period lagged levels of agreement, *Agreement*, one-period change in the level of agreement, Δ*Agreement*, natural logarithm of the number of subscribers, *Subscribers*, as well as the average number of submission thumbs-up, *ThumbsUp*. We include a binary variable, *Fiat*, that equals one if the deposit was made in fiat, and zero otherwise. We also include trader-specific variables that are calculated up to but not including time t, such as the cumulative rolling average of a trader's trading performance, ROI_{Career}, cumulative number of trades, *Trades*, count of unique assets traded, *Assets*, average trade size, *Size*, mean balance, *Balance*, and the volatility of the cryptocurrency market, *Volatility*, proxied by the standard deviation of hourly returns of BTCUSD over a one week window. We control for country of residence, and age, *Age*. All models include trader and asset fixed-effects. We report the number of observations, N, the adjusted R^2 for the linear model, the pseudo R^2 for the logistic model, and the concordance index for the AG model.

	Model (3.a)			**Model (3.b)**			**Model (3.c)**		
	Coef.	**S.E.**		**Coef.**	**S.E.**		**Coef.**	**S.E.**	
$Bullishness_t$	-46.630	3.219	***	2.127	0.982	**	0.226	0.018	***
$Bullishness_{t-1}$	1.158	2.123		0.497	0.775		-0.014	0.018	
$\Delta Bullishness_{t,t-1}$	0.029	0.031		0.161	0.012	***	0.003	0.001	***
$Agreement_t$	32.847	5.030	***	37.041	6.388	***	6.010	2.204	***
$Agreement_{t-1}$	-3.122	2.920		3.211	2.448		1.505	1.332	
$\Delta Agreement_{t,t-1}$	0.082	0.010	***	0.040	0.004	***	0.003	0.001	***
$Subscribers_t$	-1.053	0.060	***	0.209	0.019		-0.04	0.004	***
$ThumbsUp_t$	0.278	0.026	***	0.280	0.008	***	0.006	0.001	***
$Fiat_t$	2.224	0.326	***	-0.321	0.01	***	-0.421	0.01	***
$ROI_{Career,t}$	-1.434	0.150	***	-2.953	0.053	***	0.372	0.034	***
$Trades_t$	$3.0e^{-5}$	$2.2e^{-6}$	***	$3.4e^{-5}$	$2.3e^{-6}$	***	$2.0e^{-5}$	$1.9e^{-6}$	***
$Assets_t$	0.049	0.004	***	0.073	0.008	***	0.008	0.001	***
$Size_t$	$3.3e^{-6}$	$3.1e^{-6}$		$3.2e^{-6}$	$7.0e^{-6}$		$-3.7e^{-8}$	$2.8e^{-7}$	
$Balance_t$	$3.9e^{-5}$	$1.9e^{-6}$	***	$5.5e^{-5}$	$3.3e^{-6}$	***	$7.6e^{-6}$	$3.0e^{-7}$	***
$Volatility_t$	0.008	$1.2e^{-4}$	***	0.003	$3.4e^{-5}$	***	0.003	$1.2e^{-5}$	***
Age	0.002	$1.0e^{-4}$	***	0.002	$7.3e^{-5}$	***	$-1.1e^{-4}$	$1.5e^{-5}$	***
Age^2	$-2.2e^{-5}$	$1.2e^{-6}$	***	$-2.1e^{-5}$	$2.0e^{-6}$	***	$3.3e^{-6}$	$1.1e^{-6}$	***
N	39,138			39,138			39,138		
$(Adj.\vert\, Pseudo)\, R^2$	37.9%			7.56%					
$Concordance$							71.1%		

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 5: **Sentiment and Withdrawals.** This table shows the results of models examining the impact of sentiment on traders' decision to withdraw funds. Model (4.a) is linear and uses the natural logarithm of the withdrawn funds at time t valued in USD as the dependent variable. Model (4.b) is logistic and uses a binary dependent variable that takes the value of one if the trader makes a withdrawal, and zero otherwise. Model (4.c) is the Andersen-Gill (AG) model where the outcome variable is the time since entry into the sample until a withdrawal has occurred. Independent variables include parameters that quantify the sentiment of submissions, including contemporaneous and one-period lagged bullishness levels, $Bullishness$, one-period change in bullishness, $\Delta Bullishness$, contemporaneous and one-period lagged levels of agreement, $Agreement$, one-period change in the level of agreement, $\Delta Agreement$, natural logarithm of the number of subscribers, $Subscribers$, as well as the average number of submission thumbs-up, $ThumbsUp$. We include a binary variable, $Fiat$, that equals one if the withdrawal was made in fiat, and zero otherwise. We also include trader-specific variables that are calculated up to but not including time t, such as the cumulative rolling average of a trader's trading performance, $Career_{ROI}$, cumulative number of trades, $Trades$, count of unique assets traded, $Assets$, average trade size, $Size$, mean balance, $Balance$, and the volatility of the cryptocurrency market, $Volatility$, proxied by the standard deviation of hourly returns of BTCUSD over a one week window. We control for country of residence, and age, Age. All models also include trader and asset fixed-effects. We report the number of observations, N, the adjusted R^2 for the linear model, the pseudo R^2 for the logistic model, and the concordance index for the AG model.

	Model (4.a)			**Model (4.b)**			**Model (4.c)**		
	Coef.	**S.E.**		**Coef.**	**S.E.**		**Coef.**	**S.E.**	
$Bullishness_t$	1.472	2.189		1.589	0.351	***	0.371	0.181	***
$Bullishness_{t-1}$	0.57	1.423		0.625	0.804		0.049	0.17	
$\Delta Bullishness_{t,t-1}$	0.005	0.020		0.193	0.013	***	0.002	0.002	
$Agreement_t$	-38.482	35.824		-33.979	9.752	***	-3.687	1.101	***
$Agreement_{t-1}$	-4.526	3.993		-4.345	4.110		-1.231	0.941	
$\Delta Agreement_{t,t-1}$	-0.002	0.007		-0.011	0.004	***	-4.1e^{-4}	0.001	***
$Subscribers_t$	0.381	0.040	***	-0.010	0.020		-0.002	0.004	
$ThumbsUp_t$	0.110	0.018	***	0.237	0.009	***	0.003	0.001	***
$Fiat_t$	3.771	0.423	***	-0.574	0.01	***	-0.398	0.111	***
$ROI_{Career,t}$	-0.152	0.055	***	-2.660	0.168	***	-0.101	0.009	***
$Trades_t$	$-3.3e^{-5}$	$1.1e^{-5}$	***	$-2.7e^{-5}$	$3.1e^{-6}$	***	$-1.1e^{-5}$	$1.0e^{-6}$	***
$Assets_t$	0.02	0.003	***	0.087	0.002	***	-0.006	$3.0e^{-4}$	***
$Size_t$	$2.6e^{-6}$	$3.5e^{-6}$		$2.0e^{-6}$	$3.1e^{-6}$		$-4.4e^{-8}$	$9.3e^{-7}$	
$Balance_t$	$3.5e^{-5}$	$5.2e^{-6}$	***	$4.2e^{-5}$	$2.3e^{-6}$	***	$-5.2e^{-5}$	$7.0e^{-7}$	***
$Volatility_t$	-0.003	$1.2e^{-4}$	***	-0.004	$3.7e^{-5}$	***	-2.5e^{-4}	$1.0e^{-5}$	***
Age	$9.1e^{-4}$	$6.6e^{-5}$	***	0.003	$1.0e^{-5}$	***	-1.8e^{-4}	$3.0e^{-5}$	***
Age^2	$-4.0e^{-6}$	$3.3e^{-7}$	***	$-2.8e^{-4}$	$1.7e^{-5}$	***	$2.8e^{-6}$	$1.5e^{-7}$	***
N	34,957			34,957			34,957		
$(Adj.\|\,Pseudo)\,R^2$	35.1%			9.47%					
$Concordance$							73.4%		

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$