THE ROLE OF BEHAVIOURAL BIASES AND PERSONALITY TRAITS OF RETAIL INVESTORS IN ICOS

Research paper

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Abstract

Following a significant increase in media attention through the exorbitant rise in Bitcoin prices in 2017, the Initial Coin Offering (ICO) was introduced as a new way for organisations and companies to fund their business, while retail investors were presented with a new opportunity to invest into young projects and companies. Little is known about who these investors are, why and how they invested in ICOs and how they evaluated their investments afterwards. Thus, in this paper, we investigate how investment behaviour and investment satisfaction is influenced by behavioural biases and personality traits of retail investors in ICOs. We analyse survey data from more than 300 respondents, finding that ICO investors are young, educated and in the majority male. Significant relationships between single biases and personality traits can be found. Investors demonstrate a unique set of personality traits, scoring low on neuroticism, which may explain consciously made, high-risk investments. Additionally, biases affect investment satisfaction, with overconfidence and disposition bias surprisingly being positively associated with investment satisfaction. Our results may help investors understand and improve their investment behaviour and decisions, while regulators may use this knowledge to assess the need to protect investors from costly mistakes in a new, technology driven market.

Keywords: Cryptocurrency, ICO, Initial Coin Offering, Bitcoin, Personality traits, Behavioural Biases

1 Introduction

In the middle of 2017, the atmosphere of a worldwide goldrush arose in the area of cryptocurrencies. The rapid increase in prices of Bitcoin, Ethereum et cetera not only dominated the media landscape but also led to a sharp rise in the awareness of cryptocurrencies among the population. Retail investors speculated - seemingly lacking any understanding or knowledge of the risk involved - with cryptocurrencies and related projects in pursuit of fast and high returns on their investments and access to potentially disrupting companies and technologies. In addition to buying well-known currencies such as Bitcoin at the few relatively established crypto exchanges, a new form of subscription of shares or tokens was introduced in the crypto-ecosystem, the so-called Initial Coin Offerings (ICO). In contrast to other asset classes and funding methods, the execution of and investment in an ICO is still hardly regulated and thus offers legal uncertainty for the investor as well as increased fraud potential. Despite these factors, companies were able to raise over $9 billion through token sales in the first quarter of 2018 alone ("Coinschedule - Cryptocurrency ICO Statistics. (2018)," n.d.), clearly outperforming other alternative investment models for retail investors such as crowdfunding ("Crowdfunding," n.d.) and crowdlending (“Crowdlending (Business),” n.d.) in terms of money invested. While the ICO-operating companies are looking for investors and therefore act more or less transparently and provide - sometimes falsified - information, there is, to the best of our knowledge, hardly any information about the investors, their motivation and investment behaviour. Research on ICOs is mainly being done from a regulatory perspective (Dell’Erba, 2017) or in order to evaluate their investment performance (Chanson, Risius, & Wortmann, 2018), all the while the crypto industry continues to grow and is subject to strong, quick and continuous change. Research and scientific work are not only needed due to the sheer size of the market, but also to provide insights and suitable starting points for possible regulation to protect retail investors from potential frauds and scams. In this paper, we aim to answer the question of who invests in ICOs by evaluating the personality traits (PT) and socio-demographics of actual retail investors into token offerings by using known instruments such as the Big Five (B5) personality test. Additionally, we evaluate the investors satisfaction with their investments and evaluate whether retail investors exhibit behavioural biases (BB) that influence their satisfaction, leading to non-optimal investment decisions. We conduct this assessment of retail investors' behaviour in order to provide insights for regulating authorities to decide whether stricter regulation might be necessary to enhance consumer protection in the future. Furthermore, such analyses can enable investors to become aware of potential biases and critically reflect on their investment behaviour. Therefore, the following research questions (RQ) are proposed:

RQ1: What are the personality traits of retail investors in ICOs and is there a relationship between personality traits and behavioural biases?

RQ2: How do behavioural biases and personality traits influence the satisfaction of retail investors with their ICO investment?

We focus our empirical study on retail investors as they are targeted by companies and projects conducting an ICO as potential investors. Retail investors generally have fewer opportunities to invest in a company or project at an early stage. While professional and institutional investors are able to invest as an angel investor or through venture capital, retail investors are limited to the relatively new forms of investing, crowdfunding and crowdinvesting. On the other hand, ICOs have not been suitable as an investment opportunity for institutional investors due to their unregulated nature and unidentifiable risk – reward profile which is why we focus on retail investors in this paper. We define a retail investor through the Farlex Financial Dictionary as “An investor who invests small amounts of money for himself/herself rather than on behalf of anyone else” (“retail investor,” 2009).

The remainder of the paper is as follows. Section 2 summarizes relevant knowledge on the related field of behavioural finance, the different behavioural biases and analysed the personality traits. Section 3 presents the results of a systematic literature review on related work. Section 4 illustrates the methodology. We present and discuss our results for the two research questions in Section 5. Section 6 concludes the article by discussing limitations and opportunities for future work.

2 Theoretical Background

In this Section, we briefly describe the related research field of behavioural finance and the heuristics and biases influencing investment behaviour. In addition, we provide definitions of the personality traits and summarise investment specific results related to these traits.

2.1 Heuristics and Biases

The field of behavioural finance emerged as a response to the traditional economic theory of the rational investor (Wahren, 2009) and the Efficient Market Hypothesis (EMH) developed in 1970 by Eugene Fama. The EMH requires agents to make rational decisions, meaning that new information is processed correctly, and that choices and behaviour is normatively correct (Fama, 1970). However, as empirical evidence demonstrates, individuals do not generally behave rationally, their actions are not optimal and information is not correctly interpreted and acted upon (Barber & Odean, 2013). The field of behavioural finance investigates the mistakes that individuals make in their financial decisions and tries to find reasons for irrational behaviour or market inefficiencies, and analyses how market participants use this to their advantage. Behavioural finance can be viewed as a subarea of behavioural economics which researches the effect of social, cultural and psychological factors on the decision making of market participants (Lin, Chiu, & Kang, 2010). Adam Smith's lesser known work Theory of Moral Sentiment (Smith, 1759) describes the struggle of a person's decision making and can be seen as an introduction to behavioural economics (Widger & Crosby, 2014). Daniel Kahneman and Amos Tversky introduced the famous Prospect Theory in 1979, whose idea of decision making under uncertainty is widely regarded as the starting point of behavioural economics (Widger & Crosby, 2014).

In general, it is simply impossible for individuals to collect and process all information they would require in order to make the objectively best decision. First, there is far too much information available while the individuals are under constant time and performance pressure. Secondly, they lack the knowledge to process the information properly. Thus, individuals make use of heuristics to reduce the complexity of a situation and to decide whether or not to invest in an asset.

Heuristics are defined as rules or strategies to process information without the requirement of great effort which lead to fast but not necessarily optimal results (Goldberg & Von Nitzsch, 2004). Heuristics are being used either consciously or subconsciously in order to save time or costs as well as effort. These heuristics, also called biases, are being studied in behavioural finance to determine how and why individuals make certain, suboptimal financial decisions (Daxhammer & Facsar, 2017). In this study, we assess the impact of such biases for retail investors that invest in ICOs. Many heuristics and biases interact with each other, making their identification and categorization difficult. However, the literature roughly differentiates between a set of heuristics and biases summarized in Table 1, which we analyse in our empirical analysis in Section 5. Table 1 defines these biases, and states their outcome and empirical findings in an investment specific context.

	Description
Availability Bias (A)	<u>Definition:</u> Information that is not readily or not at all available will be neglected in the decision-making process and individuals remember information from their personal experience, preferences or recent happenings (Tversky & Kahneman, 1974). <u>Outcome:</u> Systematic misjudgement of probabilities and a distortion of perception by the individual (Tversky & Kahneman, 1974). <u>Investment-Specific Result</u>: Retail investors are net buyers of stocks that are prominent in the news, heavily traded or with extreme short time return. Thus, attention-grabbing stocks are traded more than stocks of companies in the same industry that received less attention (Barber & Odean, 2013). Retail investors have limited time available to make decisions. Since they cannot evaluate all information on all stocks, they focus their decision-making on stocks that they already have information on or that are prominent in their mind (Tversky & Kahneman, 1973).
Herding Behaviour (H)	<u>Definition</u>: Herding can be described as "buying (selling) simultaneously the same stocks as others buy (sell)..." (Lakonishok, Shleifer, & Vishny, 1992, p.23). <u>Outcome</u>: Non-optimal decision making and excessive trading <u>Investment-Specific Result:</u> Herding behaviour can be found extensively in investors (see Kumar & Lee, 2006; Burghardt, 2011) that follow the actions of other investors, as they believe that the actions of other investors are due to a better knowledge of the specific situation.
Representativeness Bias (R)	<u>Definition:</u> Probabilities are subjectively assessed. It is defined as "... a tendency to assess the similarity of outcomes, instances and categories on relatively salient and even superficial features, and then to use these assessments and similarity as a basis of judgement" (Gilovich, 1991, p.18). <u>Outcome:</u> Misjudgement of probabilities <u>Investment-Specific Result:</u> The pure listing of companies in segments in which other companies were able to achieve extremely high subscription profits lead to high profits in their listings (as happened during the "new economy" bubble in Germany in the years 2000 and 2001) (Taffler, 2010). Similarly, people tend to evaluate the future performance of a stock based on its historical performance, disregarding other variables.

Mental Accounting* (M)	Definition: Individuals categorize their assets depending on their purpose, investment time frame or source of income (Pompian, 2006; Thaler, 1999). Mental accounting is linked to the Prospect Theory through which each individual tries to maximise utility, whereby the initial buying price acts as the reference point (Daxhammer & Facsar, 2017). Through mental accounting, the different investments are separated or integrated mentally into one another to maximise the perceived joy about their investment decisions. Profits are hereby evaluated separately and losses are aggregated and sold to increase joy or avoid regret. Investment-Specific Result: Non-optimal investment decisions and a decrease in diversification
Overconfidence Bias (O)	Definition: Individuals are more confident in their own abilities, knowledge or judgement than what is objectively accurate. There are three types of overconfidence: overestimation (belief that you are better than you truly are), overplacement (belief that you are better than others) and overprecision (belief that you know the truth) (Moore & Schatz, 2017). Overconfidence and excessive trading are especially present in single men (Barber & Odean, 2001). Dittrich, Güth and MacIejovsky (2005) showed that the more complex the investment portfolio of an individual, the higher the degree of overconfidence. Outcome: A lack of planning and the tendency to invest into assets that they know too little about (Belsky & Gilovich, 2010). In IPOs, overconfidence lead to negative returns for retail investors (Neupane & Poshakwale, 2012). Investment-Specific Result: Investors may not only be overconfident in their abilities or the quality of their information, leading to excessive trading and thus to suboptimal returns (Odean, 1998).
Confirmation Bias (C)	Definition: Tendency to only confirm one's beliefs regardless of whether these beliefs are objectively true or not (Armstrong & Plous, 1994). Outcome: The individual exclusively searches for additional information that supports his own hypothesis and avoids evidence that would contradict their belief in order to confirm and strengthen made decisions and to avoid emotional pain due to wrong decisions (Albarracín & Mitchell, 2004). Investment-Specific Result: Park, Konana, Gu, Kumar and Raghunathan (2012) found that investors exhibit confirmation bias when they look at stock message boards and that confirmation bias leads to an increase in overconfidence bias. Duong, Pescetto and Santamaria (2014) showed that investors over- or underreacted to financial information due to confirmation bias.
Disposition Bias (D)	Definition: Investors are risk averse when it comes to profits and risk seeking when it comes to losses (Shefrin & Stratman, 1985). Outcome: People value gains differently than their losses, selling profitable assets too early and holding non-profitable assets for too long (Kahneman & Tversky, 1979). Investment-Specific Result: Evidence for the disposition effect has been found both in institutional as well as retail investors (see Ferris, Haugen, & Makhija, 1988; Garvey & Murphy, 2004; Odean, 1998) resulting in a decrease in return on investment.

Table 1. Heuristics and Biases from the Behavioural Economics and Finance Discipline (Phenomena Exclusive to the Behavioural Finance discipline are marked with an Asterisk)

2.2 Personality traits

Personality is described as the characteristic patterns and differences of thinking, feeling and behaving of individuals (Kazdin, 2000). While individuals differ in their personality, certain traits or dimensions of personality are measured and defined in order to study the difference in individuals and personality types. The Big Five personality traits, or five-factor model (FFM) is one of the most used models to measure personality by defining five main factors. These five factors, defined by Norman (1963) can be seen in Table 2 as well as their link to specific investment behaviour.

Personality has been used in behavioural finance to find and explain differences in financial behaviour of individuals. Durand, Newby, Tant and Trepongkaruna (2013) studied the relationship of investor behaviour and personality and found that "... personality is the wellspring of investors' behaviour.". Rizvi and Fatima (2015) showed in an exploratory study that all the Big Five personality dimensions had a significant impact on stock market investment and linked them to socio-demographics. Personality traits are not completely separated from each other (Anusic, Schimmack, Pinkus, & Lockwood, 2009) and various correlations between traits exist, e.g. extraversion correlates with neuroticism and conscientiousness (Gnambs & Batinic, 2012).

	Description
Open-ness (OP)	Definition: Openness relates to general curiosity, an interest and appreciation to new experiences, emotions, art, adventures and new ideas (McCrae, Costa & Martin, 2005). Individuals that score high on openness have a strong imagination and are flexible in their behaviour. In investors, openness also relates to risky behaviour or gambling. Investment-Specific Result: Openness was found to be connected to the gathering of information as it is related to natural curiosity and the interest in creating new experiences (Costa & McCrae, 1992). Open individuals therefore acquire much information from multiple sources (Kasperson, 1978). Open minded individuals are also found to be critical thinkers, reflecting on the information that they gathered (Heinstrom, 2010, p.18). Openness, as well as emotional stability are also linked to high risk acceptance in successful professional traders (Fenton-O'Creevy, Nicholson, Soane, & Willman, 2011) and to long-term investing (Mayfield, Perdue, & Wooten, 2008). Kleine, Peschke and Wagner (2019) found that individuals that invest in collectibles, another non-traditional investment, scored higher on openness than a control group.
Extra-version (EV)	Definition: Extraversion describes the tendency to be outgoing and sociable (John & Srivastava, 1999). Individuals that score high on extraversion may seek attention of others. Investment-Specific Result: Extraversion was found to influence financial preferences as well as investment performance and choices (Durand et al., 2013; Oehler & Wedlich, 2017). Mayfield, Perdue and Wooten (2008) found that extraversion is linked to short-term investing, while Durand et al. (2013) linked it to overconfidence.
Agree-able-ness (AG)	Definition: Agreeableness is seen as being compassionate and trusting towards other people. A low score on agreeableness may show competitive behaviour or an untrustworthy individual. Investment-Specific Result: Agreeableness is found to be related to risk aversion (Dohmen et al., 2011) and associated with a decreased likelihood of investing in higher risk investments, e.g. shares (Brown & Taylor, 2014).
Neurot-icism (NE)	Definition: Neuroticism is the tendency to experience negative emotions and being stressed out easily. Low scores on neuroticism relate to a high control over the individual's emotions. Investment-Specific Result: Andreas Oehler, Wendt, Wedlich and Horn (2018) found that neuroticism in business student investors leads to a less risky investment portfolio. Similarly, high neuroticism is linked to being less able to manage money compared to highly conscientious individuals (Donnelly, Iyer, & Howell, 2012). Additionally, Gambetti and Giusberti (2012) found that anxiety which is linked to neuroticism is negatively associated with stock trend predictability. (Durand et al. (2013) could show in their study that neuroticism is linked to frequent trading, as investors are less anxious about their trading results.
Consci-en-tious-ness (CC)	Definition: Conscientiousness describes the tendency to be orderly, responsible and dependable (John & Srivastava, 1999). Investment-Specific Result: Conscientiousness was found to be the most important personality trait for money management and self-control regarding financial behaviour. Donnelly et al. (2012) showed that conscientious individuals have a more positive financial attitude and future orientation.

Table 2. Personality traits and their relation to financial behaviour

3 Related Work on ICOs

The Initial Coin Offering is the first public offering of a crypto token and the first possibility for retail investors to invest in a company and their crypto-token. The fundraising company offers newly created tokens in exchange either for fiat currency or for existing tokens like Bitcoin or Ethereum (see Fridgen, Regner, Schweizer, & Urbach, 2018). The first ICO was held in 2013 by the Mastercoin foundation, now known as Omni (Zynis, 2013). In 2014, the cryptocurrency Ethereum raised money through a specific ICO process which became the technological standard for most ICOs to come. In 2018, more than 80% of all ICOs were raised through the Ethereum blockchain by using a technical standard called ERC-20 which defines smart contracts on the Ethereum blockchain to implement tokens (Fenu, Marchesi, Marchesi, & Tonelli, 2018). ICOs became known to the wider public in 2017 with the strong increase in Bitcoin and other token prices (Adhami, Giudici, & Martinazzi, 2018). The amount raised through ICOs increased from about \$616,000 in 2013 to around \$5.3 billion in 2017 (Adhami et al., 2018) and about \$11.4 billion in 2018 (Pozzi, 2019). While there are no official statistics on how many ICOs have been executed, countless websites are tracking ICOs, counting more than

5000 ICOs until early 2019. The US ranks on top, both in total number of ICOs and in the amount raised (Pozzi, 2019).
In order to provide a comprehensible overview of prior literature on ICOs, we conducted a systematic literature review on ICOs in the information systems (IS) domain (vom Brocke et al., 2009). We focused on a representative selection of high quality IS journals and conferences, including the eight journals of the AIS Senior Scholars' Basket (Association for Information Systems, 2011) as well as five main IS conferences (AMCIS, ECIS, HICSS, ICIS and PACIS). We also conducted a backward search based on the final hits of the found literature in order to augment our results furthermore.
The keyword search, using "ICO" and "Initial Coin Offering" as keywords, generated only six final hits; i.e. papers which focused specifically on ICOs. The subsequent backward search generated an additional 22 papers, not only limited to IS outlets. We refrained from focusing only on IS outlets in the backward search in order to have analyse more potentially relevant articles in this relatively new field of research. Eleven papers in the backward search can be attributed to legal research (see Dell'Erba, 2017; Robinson, 2017). These articles review the legal status of an ICO and provide recommendations regarding future regulation and legislation. The remaining papers can be attributed to two main topics, namely taxonomy and general information on ICOs and the success factors of an ICO. Three articles provide a taxonomy on ICOs through expert interviews, literature reviews and past ICO data (Chanson, Risius, & Wortmann, 2018; Fridgen et al., 2018; Lausen, 2019) whereas four other articles focus on identifying the success factors of an ICO (Adhami et al., 2018; Amsden & Schweizer, 2019; Chanson, Risius, Gjoen, & Wortmann, 2018; J. W. Park & Yang, 2018). Specific to investment decisions are the articles by Amsden and Schweizer (2019) and Yadav (2018) which identify success factors that can be used by potential investors in order to evaluate whether an ICO would be a suitable investment. In contrast, Conley (2017) focuses on the issuer side and gives recommendations on what to consider when setting up an ICO.
In summary, there is – to the best of our knowledge – no research on the investor, or user of crypto tokens and ICOs in the IS domain. While price and blockchain data is largely available due to the inherent nature of cryptocurrencies, data on investors and their characteristics and perceptions does not exist. The first Know-Your-Customer (KYC) compliant ICO was held by Blockchain Capital in April 2017 (Kaal & Dell'Erba, 2017). Therefore, not even the companies themselves knew exactly who had invested in their ICO if they had not implemented KYC requirements.

When looking at cryptocurrency in general, two surveys from the companies *Circle* and *etoro* could be found which address this knowledge gap by evaluating the demographics of the owners of cryptocurrencies (Agarwalla, 2018; "Who are the Crypto Investors?," 2018) Cryptocurrency owners or users are found to be overwhelmingly male with only 8.5% being female, novice investors ("Who are the Crypto Investors?," 2018). Younger investors are found to be more risk tolerant and aggressive investors than older generations (Agarwalla, 2018).

4 Methodology

We conducted a quantitative online survey in order to obtain information on retail investors investment behaviour in ICOs, as well as their personality traits. The survey did not need an approval of an ethics committee as it qualified for exempt status according to the guidelines and a checklist provided by the ethics committee of the Goethe University Frankfurt am Main, Germany. To avoid cluster risk within the group of individuals who have invested in at least one ICO, a questionnaire was published in various online communities on different platforms over the course of January 2019. The channels used to publish the survey have been social media sites such as reddit.com, which is the most active source of information on cryptocurrencies (Bukovina & Martiček, 2016), as well as Facebook, LinkedIn and cryptocurrency related forums such as Bitcointalk.org. The survey has been advertised multiple times, and at different times of day in order to address individuals from different time zones and countries. This was done in order to obtain a representative sample of individuals, as we expected investors coming from e.g. Facebook to differ from respondents coming from a business network such as LinkedIn in terms of socio-demographics as well as in their investment behaviour and personality traits. Nonetheless, a potential selection bias cannot be fully mitigated as the demographics of Facebook and LinkedIn users and especially that of the users of cryptocurrency related forums may differ from the general population of retail ICO investors, only capturing those that engage in online discussions via these specific channels or search for information online.

We adapted the questions for BB from existing behavioural finance literature (Pompian, 2006) as well as from literature on the investment behaviour of equity investors (Alrabadi, Al-Abdallah, & Aljarayesh, 2018; Anum et al., 2015; Chandra & Kumar, 2011; Mishra & Metilda, 2015). Questions originally designed for stock market investments by Alrabadi, Al-Abdallah, & Aljarayesh (2018) regarding the seven BBs have been adapted to ICO investments and were redesigned based on the information on BB seen in Table 1. Due to the seven biases that are to be tested for and the many different facets of each bias, each item tested for one specific aspect of a bias, with three or two questions per bias. This is best explained by looking at the overconfidence bias (O), that was tested for using three items. Item O1 ("I feel that I can, on average, predict future token prices worse than others") tests for the "better than average" effect, while the remaining two items on this bias test for the "illusion of control" (O2: "I attribute my investment success to my knowledge and understanding of the crypto market") effect. Both effects are summarized in the overconfidence bias and have been studied in previous surveys (Glaser & Weber, 2007). This has been done to evaluate possible differences within a bias itself later on. The average per bias and trait was then calculated based on the average of the items per bias.

5 Results

A total of 540 persons started the survey, of which 327 successfully finished the survey, accounting also for repeat participation and control questions. Of these completes, not all participants answered each question, e.g. the age or country of origin were not mandatory to fill out to increase the level of anonymity of respondents if requested. We measured PT and BB with a 5-point Likert scale.

5.1 Descriptive Results

Table 3 shows the demographics of our sample. The overwhelming majority of respondents was male with a mean age of under 32, which is in line with findings by Agarwalla (2018) on cryptocurrency users and the fact that especially young men are empirically less risk averse in their investment behaviour (Jianakoplos & Bernasek, 1998). The majority of respondents originated from European countries. 76.4% of respondents hold a university degree, making investors a highly educated group of individuals.

Sex	#	%	Continent	#	%
Male	304	93%	Europe	197	60.2%
Female	11	3.4%	Asia and Oceania	46	14.1%
No answer	12	3.7%	Africa	14	4.3%
Age			North America	63	19.3%
Minimum	17		South America	3	0.9%
Maximum	59		Education	#	%
Mean	31.88		No school degree	8	2.4%
N	322		High School	69	21.1%
			Bachelor's	129	39.4%
			Masters's	105	32.1%
			Phd, MBA or equivalent	16	4.9%

Table 3. Descriptive statistics on retail investors

5.2 Personality Traits and Behavioural Biases of ICO Retail Investors

In this study, personality is tested for by using the BFI-10 test, introduced by Rammstedt and John (2007) in the enlarged version consisting of eleven questions. It tests for the Big Five personality traits

(B5) and is able to provide substantial reliability and validity, despite its small size. We evaluated personality traits by conducting several correlation tests. Descriptive statistics were used to compare the personality traits in this paper to results of former research. It can be seen in Table 4 that, amongst all respondents, conscientiousness is the personality type most pronounced (mean equals 3.57), closely followed by agreeableness and openness. Neuroticism is the least pronounced personality type by far. Several correlations between traits can be observed, similarly to findings made by (Gnambs & Batinic, 2012). Especially neuroticism demonstrates a negative correlation to extraversion, conscientiousness and agreeableness. In contrast to that, extraversion is found to correlate positively to conscientiousness. All other correlations are not statistically significant. Regarding BB, overconfidence exhibits the highest (3.66) and herding behaviour the lowest (2.55) mean. Correlations are found between representativeness bias and availability bias, as well as herding and mental accounting. Interrelation between biases has been found in behavioural finance by Agrawal (2012) who found that biases may reinforce each other.

Traits	Total	Mean	Std. dev.	OP	EX	CC	NE	AG		
OP	301	3.45	.89	1	.06	.107	-.112	.003		
EX	301	3.11	.96		1	.148*	-.240**	.037		
CC	301	3.57	.80			1	-.205**	.110		
NE	301	2.56	.94				1	-.149**		
AG	301	3.50	.75				-	1		
Biases	Total	Mean	Std. dev	O	C	D	R	A	M	H
O	327	3.66	.61	1	,02	,08	,01	-.08	-.07	-.07
C	327	2.93	.64		1	-,05	.09	.05	.05	.05
D	327	2.91	.63			1	-.10	-.095	.04	.37
R	327	2.74	.59				1	.17**	.13*	.20*
A	327	3.00	.68					1	.13*	.26**
M	327	3.22	.72						1	.19**
H	327	2.55	.84							1

*. Pearson Correlation is significant at the 0.05 level
**. Pearson Correlation is significant at the 0.01 level

Table 4. Descriptive statistics and correlations on personality and biases

Using Friedman's Chi-Square as a reliability analysis, a statistically significant difference between the PT can be seen, $\chi^2(4)=165.43$, $p < .001$. Similarly, a statistically significant difference between the BB can be seen, $\chi^2(6)=423.59$, $p < .001$. However, Cronbach's Alpha demonstrated an unacceptable values below .6 (Peterson, 1994). Only extraversion demonstrates an acceptable value with 0.62, while all other traits and biases demonstrate unacceptable results. This indicates low consistency between items that measure the same theoretical concept. While these values are problematic, we decided to still employ averages of the individual items to calculate traits and biases to avoid overfitting and selection bias.

In a next step, we evaluate how the traits of retail investors influence potential biases. To do this, we replicate part of the work done for retail investors in financial markets by Kubilay and Bayrakdaroglu (2016), who researched the relationship between PT and BB, as well as between these biases and the financial risk tolerance of investors living in Istanbul who are active in the financial markets. The authors' sample consists of 89% male respondents, with the majority of investors between age 21-30, making their sample comparable to ours. However, as different biases were used, only representativeness, availability and overconfidence bias, as well as herding behaviour, can be compared. Unfortunately, no descriptive results were shown regarding biases and traits, therefore, only the Chi-Square results are comparable. Within their study agreeableness demonstrated a significant relationship with six out of seven biases, followed by extraversion with three biases. Representativeness is found to be the most common bias, while agreeableness is the trait most prone to biases, whereas individuals scoring low on neuroticism are faced with the least biases. Furthermore, the authors find that investors have a low risk tolerance.

In this study, we focus on the first interrelationship, comparing the distributions between each PT with a list of biases via Pearson's χ^2 test. The results are shown in Table 5. A significant relationship with at least one personality trait can be shown for all BB with traits except for disposition and representativeness bias. Mental accounting demonstrated a relationship with extraversion, while herding, overconfidence, conscientiousness and availability bias all demonstrated a significant relationship with at least two personality traits. Overall, every trait was associated with two biases.

Biases / Traits	Overconfidence	Confirmation	Disposition	Representativeness	Availability	Mental Accounting	Herding
OP	$\chi^2(72)=91.02$, p=.065	$\chi^2(96)=136.5$, p=.004*	$\chi^2(80)=70.92$, p=.76	$\chi^2(80)=81.39$, p=.44	$\chi^2(96)=81.16$, p=.86	$\chi^2(88)=87.1$, p=.51	$\chi^2(64)=90.99$, p=.02*
EX	$\chi^2(72)=72.76$, p=.45	$\chi^2(96)=117.8$, p=.065	$\chi^2(80)=93.9$, p=.14	$\chi^2(80)=92.65$, p=.16	$\chi^2(96)=130.30$, p=.011*	$\chi^2(88)=117.04$, p=.02*	$\chi^2(64)=72.5$, p=.22
CC	$\chi^2(72)=90.07$, p=.073	$\chi^2(96)=125.1$, p=.025*	$\chi^2(80)=65.28$, p=.88	$\chi^2(80)=96.2$, p=.11	$\chi^2(96)=145.58$, p=.001*	$\chi^2(88)=72.56$, p=.88	$\chi^2(64)=58.27$, p=.68
NE	$\chi^2(72)=108.93$, p=.003*	$\chi^2(96)=97.6$, p=.44	$\chi^2(80)=87.91$, p=.26	$\chi^2(80)=89.7$, p=.22	$\chi^2(96)=100.88$, p=.35	$\chi^2(88)=76.82$, p=.80	$\chi^2(64)=88.63$, p=.023*
AG	$\chi^2(99)=131.14$, p=.017*	$\chi^2(132)=138.75$, p=.33	$\chi^2(110)=97.63$, p=.8	$\chi^2(110)=113.45$, p=.39	$\chi^2(132)=189.53$, p=.001*	$\chi^2(121)=117.12$, p=.58	$\chi^2(88)=100.84$, p=.17

Table 5. Chi-Square analysis on behavioural biases and personality traits

In a direct comparison to Kubilay and Bayrakdaroglu (2016), we only find similar results in the significant relationship between agreeableness and availability bias, as well as agreeableness and overconfidence. Kubilay and Bayrakdaroglu (2016) identified several significant relationships that have not been significant in our study. These include representativeness with EX and AG and overconfidence with EX. However, as ICOs are a very high-risk investment that may appeal to specific types of investors, the differences in findings might be explained through the unique personality type of those investors.

Through Cronbach's Alpha, it became apparent that the items regarding the same BB may be measuring different theoretical concepts. In order to investigate whether BB, as well as PT interact with each other as different components of the same theoretical concepts, a Principal Component Analysis (PCA) has been performed in order to find the most important independent factors. PCA offers feature extraction and dimensionality reduction, meaning the reduction of possible variables in order to find the most important variables in a large set of variables. Instead of simply aggregating questions that have been designed to test for the same bias in other papers, the PCA is used in an exploratory manner to find out which items fit well with each other, based on the respondent's answers. The results are factors that are loaded with different items. Chandra and Kumar (2011) used PCA to investigate BB of stock market investors and were able to identify five psychological axes that are driving individual investor behaviour, using 17 items on BB.

The PCA in this study consists of all BB questions individually, as well as the five PT to evaluate whether and how the two interact. In total, 24 components have been reduced to six factors. The Kaiser–Meyer–Olkin measure of sampling adequacy was .687, an acceptable value for factor analysis (Kaiser, 1974). Bartlett's test of Sphericity was significant ($p < .001$), which indicates that the correlation between items was sufficient for the analysis. These values support the view that the PCA is a suitable method for the existing data. Only factors with eigenvalues > 1 were considered (Kaiser, 1960) in the first factor analysis, while in the second factor analysis six factors were chosen as components, using the scree-plot as justification. These six factors accounted for 46.55% of the total variance. The items per bias as well as total traits are shown in Table 6 with their loadings, grouped into the six components found. As was to be expected in light of the low Cronbach's Alpha, questions which were supposed to account for the same bias did not load for the same factors. The only exception of this was the mental accounting bias, which has also been the bias with the highest Cronbach's Alpha. All questions regarding mental accounting are the only loadings for one factor, whereby two questions are loading the factor positively and one is loading it negatively. However, the remaining five factors are being loaded, positively and negatively by different BB, as well as PT. Agreeableness is not loading any factor and is, judging by the fact that there is no significant correlation with other PT, the least important PT, as all other traits are loading factors.

	Components					
	1	2	3	4	5	6
Loading (item)	.683 (R2)	.752 (D1)	.704 (CO)	.775 (M2)	-.689 (C1)	-.616 (D3)
	.647 (C3)	-.621 (R3)	.601 (O2)	.583 (M1)	.590 (C2)	.553 (EX)
	-.585 (D2)	.570 (R1)	-.491 (NE)	-.445 (M3)	.472 (O3)	.502 (H2)
	.540 (A2)	-.540 (A3)			.440 (OP)	
	.449 (A1)	.468 (H1)				
	-.423 (O1)					
	434 (H2)					

Table 6. Rotated Principal Component Matrix

This is in contrast to Kubilay and Bayrakdaroglus (2016) who found agreeableness to be the most important trait in investors, albeit their respondents are found to be risk averse. Most importantly, different questions regarding overconfidence are loading negatively with neuroticism, as well as positive loadings with conscientiousness and openness. While there is no obvious way to name the factors, it can be observed that PT interact with BB in ICO investors. It can be seen that the questions regarding availability bias and herding behaviour, that both demonstrated a negative effect on satisfaction, are both loading the first factor together. This strengthens the point made earlier, different biases may measure similar aspects. The PCA therefore demonstrates that different biases not only interact with each other, except for mental accounting which also was the only bias not demonstrating any significant effect, but that they also interact with PT, which was also found in Table 5. Furthermore, different biases are loading the same factors positively as well as negatively, as in the example of factor six with negative disposition bias and positive herding behaviour.

5.3 Analysis of Investor Satisfaction for ICO Investments

The second research question addresses the behavioural biases of retail investors in the context of ICOs and how these biases affect investors' satisfaction. Investor satisfaction is defined by Rutkowska (2015) as the comparison of an individual's expectations to the perceived performance of an investment, representing a special type of utility function. Schwaiger, Kirchler, Lindner and Weitzel (2019) investigate satisfaction of both financial professionals and students, finding that changes in prices influence satisfaction. We ran a multivariate regression analysis of the satisfaction on the average of each BB while controlling for PT to assess whether BB influence the satisfaction investors with their ICO investment. We do this even though Cronbach's Alpha indicated low internal reliability to avoid selection bias and overfitting with too many exogenous variables. The results are given in Table 7. This regression yielded an adjusted R^2 of 0.1075, indicating a moderate exploratory power of the regression. None of the traits are significant, while Overconfidence is highly statistically significant with $p < 0.01$, and both Disposition and Confirmation bias being significant with p-values around 0.03. The sign on overconfidence is positive and has a very high absolute value, indicating that an unrealistically high degree of confidence in an investors own judgment is associated with high performance satisfaction for this investor, which is to be expected. The regression equation was the following:

$$Y_i = \beta_0 + \beta_1 EX_i + \beta_2 AG_i + \beta_3 CC_i + \beta_4 NE_i + \beta_5 OP_i + \beta_6 O_i + \beta_7 R_i + \beta_8 A_i + \beta_9 D_i + \beta_{10} C_i + \beta_{11} M_i + \beta_{12} H_i$$

	Coefficient	Std. Error	t	Sig.
(Constant)	1.2363	0.9505	1.3010	0.1944
Extraversion	0.1113	0.0741	1.5020	0.1341
Agreeableness	0.1201	0.0917	1.3100	0.1913
Conscientiousness	0.0793	0.0868	0.9140	0.3612
Neuroticism	-0.1453	0.0757	-1.9190	0.0559
Openness	0.0194	0.0767	0.2530	0.8005
Overconfidence	0.3220	0.1171	2.7500	0.0063**
Representative	0.1946	0.1158	1.6820	0.0937
Availability	-0.1479	0.1035	-1.4290	0.1540
Disposition	0.2368	0.1086	2.1810	0.0300*
Confirmation	-0.2408	0.1105	-2.1780	0.0302*
Mental Accounting	0.0139	0.0980	0.1420	0.8872
Herding	-0.0589	0.0841	-0.7010	0.4842

Table 7. Regression of average BB and traits on retail investor satisfaction in ICOs

Results in Cronbach’s Alpha demonstrated that there is low to no interrelatedness between questions measuring the same behavioural bias, as well as low interrelatedness between questions per personality type. There are several possible explanations for this finding, which are explained in the following. Questions designed specifically to test for behavioural biases have not been researched as extensively as personality traits. The questions in this survey have been adapted from questions of Alrabadi et al. (2018) where the questions regarding stock market investments all lead to good, or very good, values of Cronbach’s Alpha for each bias. As the questions were only adapted and have been verified by scientific literature in order to ensure that each question is concerned with a particular aspect and behaviour of a bias, the resulting low alphas from this survey are surprising. The fact that questions on personality traits, which were extensively proven to be interrelated, also demonstrated low Alphas, speaks for the fact that there might have been not enough questions to achieve sufficiently high Alphas.

A second possible explanation is that many questions measure different sub-biases or sub-aspects of one bias. Evidently, participants’ responses have differed between these sub-biases, as has been explained in section 4. Additionally, it has been shown that behavioural biases interact with each other and behaviour patterns can be due to multiple different biases (see Daxhammer & Facsar, 2017, p.253ff) and that the interrelatedness of biases can skew the results.

Even though Cronbach’s Alpha is low, the multivariate regression shows that the disposition, confirmation and overconfidence biases demonstrate a statistically significant effect on satisfaction. As BB generally lead to non-optimal investment performance, it was expected that BB lead to a decrease in satisfaction. While satisfaction increases with an increase in disposition and overconfidence bias, it decreases with an increase in confirmation bias. These findings are discussed in the following.

It is crucial to put the results into context with the general market environment in cryptocurrencies. The surveys took place in the month of January of 2019, which together with the preceding month saw most of the large cryptocurrencies at a two-year low after an unprecedented rally at the end of 2017. While ICOs are oftentimes highly illiquid, it is reasonable to assume they generally follow the direction of the larger crypto markets, which would imply that a majority of retail investors into ICO’s suffered losses at the time they answered the questions. Confirmation bias leads investors to seek out information that confirmed their already made decision or avoid information that would lead to changes in behaviour. As token prices have strongly and quickly decreased in 2018, confirmation bias is likely to have encouraged investors to hold their investments, instead of selling them, despite new knowledge becoming available for investors to process. This behavioural has widely been encouraged in the crypto-ecosystem through the “HODL”-trend, whereby online community members encourage each other to hold their investments, in hope of strong increases in prices, as experienced in earlier years. This behaviour is similar to findings made by Park, Konana, Gu, Kumar and Raghunathan (2012) who identified confirmation bias on stock message boards. Holding on to your investments, and ignoring a declining market, driven by news of scam and regulation or prohibition of ICOs in certain countries, is likely to have left investors with investments that are deeply in the negative. Thus, confirmation bias is found to be associated with a decrease in satisfaction, likely because investors held on to their investments for too long, which is in line with the findings stated in Table 1. This behaviour is also able to explain the results for the disposition bias which at first seems surprising.

While the disposition bias normally leads to suboptimal investment results, it might have been beneficial for ICO investors. Disposition bias leads investors sell winners to early and hold losers to long as investors are generally risk-averse when their investments are in the profit and take more risks when they are in the loss. Investors that made a profit with their ICOs quickly and are influenced by the disposition bias might have therefore sold their investments profitably, avoiding the worsening market environment in the latter half of 2018. These investors can therefore be expected to be satisfied with their investment performance. Subsequently, investors that made a profit are likely to became more overconfident, as is the nature of the self-attribution bias. While profits are attributed to one's own actions, losses are attributed to someone else, i.e. market conditions. The fact that confirmation and disposition bias show reverse trends is therefore explainable through the nature of the biases themselves, as well as the market cycle and the general sentiment in the ICO community.

Additionally, an increase in satisfaction through an increase in overconfidence bias was found. An explanation for this phenomenon may be the causality behind this specific bias, which could not be investigated further as no time-series data of the individual investors performance was available. It is possible that investors experienced high returns with their investments and, as a result of this, grew more confident. This could have led to them attributing their success to their own actions, in line with scientific findings on the bias (see Moore & Schatz, 2017; Odean, 1998). Overconfidence was expected as it is especially present in men (Barber & Odean, 2001) who make up the majority of our respondents. Additionally, it is increased by confirmation bias (Park, Konana, Gu, Kumar & Raghunathan, 2012) which was described above. On the other hand, overconfident investors might generally be more satisfied with their investment performance even in adverse situations as they assume their performance to be better compared to other investors or other investments, regardless of whether this is actually the case.

These findings demonstrate that some behavioural biases have, unexpectedly and likely unforeseen by investors, may have helped investors with their investment return, while others are associated with an decrease in satisfaction with the investment. Considering the wealth of literature establishing a link between general satisfaction and personality traits (Diener & Lucas, 1999), it is notable that in our regression, no personality trait significantly predicts investment satisfaction, with only neuroticism even breaking below a significance level of 10% percent with an expected negative sign. This shows that behavioural biases offer explanatory power for investor satisfaction beyond potentially underlying personality traits, and that satisfaction with investment performance is not simply a result of generally high life satisfaction.

6 Limitations and Future Work

The study comes with several limitations, due to its design and the novelty of the topic of research. Although the survey could reach more than 500 participants, it was taken during a strong decline in prices. The specific timing of the survey hinders reproducibility and will have likely excluded many investors that left the market with high losses for good. Investors behaviour might change in the future as early adopters and venturers leave the market and new entrants invest in regulated Security Token Offerings (STOs) that replace unregulated ICOs, changing the underlying demographic profile. Furthermore, hindsight bias might have influenced the respondent's answers about their past actions. Another clear limitation is our use of average scores even though Cronbach's Alpha showed a low degree of internal consistency for most of our variables. Future work may replicate or extend our research with a higher sample size or more items per construct for personality traits, where we restricted ourselves to a very short questionnaire. Additionally, due to the sensitive nature of this study and ICO investors, no questions regarding investment sizes or actual returns have been asked, leaving room for interpretation of the actual success of investors with their investments.

These limitations offer room for future work in the direction of cryptocurrency and ICO investors motifs, behaviour and personality. Future research may focus on single, specific biases, their interaction with personality, as well as the comparison to other asset classes.

As was shown in the PCA, biases and personality interact with each other, future studies should explore this phenomenon in more detail. A possible change in investor behaviour through the maturing of the ICO and STO market as well as a change in market participants may also be researched and evaluated. Additionally, cryptocurrency investor behaviour and personality traits could be compared to traits and personality of individuals that invested in traditional financial assets or other new forms of funding like crowdinvesting in order to identify similarities and differences between them.

7 Conclusion

For the first time, insights into ICO investors and their investment behaviour and personality have been generated. First evidence was provided that retail investors exhibit several behavioural biases that influenced their self-attributed satisfaction with their investments in the past. Hereby biases could even be attributed to an increase in satisfaction, likely due to the timing of the ICO bubble.

Retail investors were found to be overwhelmingly male, around 30 years old and exhibit a specific set of personality traits that corresponds to their risk acceptance and investment choices. Using Pearson's χ^2 test, several significant relationships between personality traits and behavioral biases could be found.

Using multiple linear regressions, evidence of behavioural biases in retail investors' investment behaviour could be found. Overconfidence, disposition and confirmation bias could be shown to have a significant effect on investment satisfaction on an aggregated bias level. Although it was hypothesised that susceptibility to behavioural biases leads to a decrease in satisfaction, it was shown that specific biases are in fact positively associated with investment satisfaction, namely overconfidence and disposition bias, and that different biases interact with each other.

Possible reasons for this investment behaviour include the very specific personality traits of ICO investors, as well as the unique circumstance of this study being conducted right after the burst of the ICO and token-price-bubble. Investors who were influenced by behavioural biases to sell their assets early, i.e. disposition bias, of course ended up being much more satisfied than investors who decided to hold on to their assets for longer than was optimal, i.e. due to confirmation bias. Regarding the remaining biases, the hypothesis that behavioural biases are associated with a decrease in investment satisfaction could be verified. Mental accounting was found not to impact investor satisfaction at all.

Additionally, using principal component analysis and analysing the relationship between behavioural biases and personality traits, we could show that behavioural biases and personality traits are loading the same factors, traits and biases interact with each other. Personality traits are found to be consistent between ICO investors and in line with scientific findings on the subject of financial behaviour.

The insights generated through this study are of value to companies that are planning on conducting an ICO, on investors and users interested in cryptocurrencies, as well as to regulators and supervisory authorities. Understanding the motifs of investors and who they are might help in the decision-making process of all aforementioned parties. The knowledge about ones behaviour and the existence of behavioural biases in the context of investment decisions might help retail investors to avoid mistakes and increase satisfaction and return. Although the knowledge about ones biases is not enough to avoid them completely, it can act as a first step to develop processes and checklists for controlled decision making (see Kahneman, Lovallo, & Sibony, 2011). It was shown that retail investors exhibit only a limited number of behavioural biases, possibly due to a specific combination of personality traits and high education. However, regulatory authorities must consider that the impact of behavioural biases and the risk of subsequent bad investments might increase substantially through a wider diffusion of cryptocurrencies and ICOs among layman users and investors.

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