Blockchain Research Lab

BRL Working Paper Series No. 6

Returns from Investing in Cryptocurrency: Evidence from German Individual Investors

Lennart Ante [1, 2, *], Ingo Fiedler [1, 2, 3], Marc von Meduna [1, 2], Fred Steinmetz [1, 2]

[1] Blockchain Research Lab, Colonnaden 72, 22303 Hamburg
[2] University of Hamburg, Faculty of Business, Economics & Social Sciences, Von-Melle-Park 5, 20146 Hamburg, Germany
[3] Concordia University, Faculty of Arts & Science, 2070 Mackay Street, Montreal, QC, H3G 2J1, Canada

* Correspondence: ante@blockchainresearchlab.org

Published: 19 Feb 2020

Abstract: Cryptocurrencies such as Bitcoin are a high-risk asset class where very high returns are offset by large losses. In a nationally representative online survey of 3,864 German citizens, 354 (9.2%) reported owning cryptocurrencies in March 2019. We analyze a subpopulation of 225 cryptocurrency owners who classify as investors. 56% of them experienced positive returns, while 29% had negative results. The remaining respondents broke even. The average investment was €1,773 in a portfolio of two cryptocurrencies. At the time of the survey, the average portfolio value had risen to €7,094 – an average gain of 300%. While nearly half of the investors (44%) outperformed Bitcoin market returns, not a single one of the early investors (2009-12) did. We find that net income, the degree of cryptocurrency knowledge and the degree of ideological motivation for owning cryptocurrency have positive effects on returns. This first scientific analysis of individual investment in cryptocurrencies provides a basis for future research and for regulatory decision-making.

Keywords: Bitcoin; Blockchain; Individual investors; Alternative investments; Financial performance

1 Introduction

Following the publication of the Bitcoin whitepaper and the subsequent launch of the Bitcoin network, the price of the digital currency rose from zero to almost $20,000 in December 2017 and then dropped back to $4,000. Thus, investing in Bitcoin is clearly risky. While Nakamoto (2008) introduced Bitcoin as electronic cash, that simple characterization no longer applies, as the benefits and applications have expanded and shifted significantly over the last ten years. Additionally, thousands of other cryptocurrencies with different focuses and features have emerged since, which are characterized by even higher returns and higher risk of loss alike. However, besides media reports about e.g. Bitcoin millionaires or total losses due to scams, comparatively little is known about the extent to which investments in cryptocurrencies have actually benefited or harmed retail investors.

Cryptocurrencies are used as digital cash, as a medium of exchange and as a store of value. Furthermore, so-called tokens, specific types of cryptocurrency, can represent additional characteristics, like vouchers, licenses, voting rights or securities (Ante and Fiedler 2019). Most cryptocurrency transactions are attributable to speculators, rather than to ‘users’ of the currency (Yermack 2015). Evidence of price bubbles underlines the speculative nature of cryptocurrencies (Corbet, Lucey, et al. 2018; Kristoufek 2018). Other research suggest that, due to the comparatively low level of regulation (cryptocurrencies are not financial instruments), price manipulation and informed trading are more likely to occur (Ante 2019; Feng et al. 2018).

Baur et al. (2018) find that Bitcoin has similarities to stocks, bonds and commodities, and suggest that Bitcoin is a speculative investment. Dyhrberg (2016) analyzes the financial asset capabilities of Bitcoin and in conclusion places Bitcoin somewhere between gold and the dollar. Other research suggests that Bitcoin has no intrinsic value at all (Cheah and Fry 2015). Exploring trading dynamics and market structures, Dyhrberg et al. (2018) show that Bitcoin is investible for retail investors.

A range of research has dealt with the adoption of cryptocurrencies as a means of payment (Schuh and Shy 2016), perceptions of cryptocurrency value (Gibbs and Yordchim 2014), the determinants of interest in cryptocurrencies (F. Glaser et al. 2014), speculative opportunities (Hur et al. 2015), the choice of specific cryptocurrencies (Al Shehhi et al. 2014) and the relationship between cryptocurrency trading and gambling (Mills and Nower 2019). Few studies have so far dealt with individual investors in cryptocurrency, but they have examined issues related to investors into initial coin offerings (ICOs), blockchain-based crowd-financing of startups (Ante et al. 2018). (Fisch et al. (2019) focus on the investment motives of 517 ICO investors and find that technological motives are most important, followed by financial and ideological motives. Fahlenbrach and Frattaroli (2019) analyze ICO investment behavior based on Ethereum wallet data, finding that large investors buy their positions at a discount and sell them profitably. However, none of these studies use population data on the socioeconomic background of cryptocurrency investors and their actual returns. To date there is no research on the performance of individual investments in cryptocurrency.

This paper aims to extend the literature on cryptocurrencies, their adoption and the question as to whether cryptocurrencies are suitable investments by characterizing cryptocurrency investors and the outcomes they achieve. We investigate whether investment success in cryptocurrency is subject to similar explanatory factors as investment in similar asset classes. Our data basis is derived from on a representative online survey among the German adult population that comprises 3,864 individuals. 354 (9.2%) of the respondents reported owning cryptocurrencies, but some of them 1) obtained their cryptocurrency not through investment but e.g. through mining or 2) failed to provide sufficient information. This leaves a group of 225 (5.8%) individual cryptocurrency investors. We address questions regarding socio-demographics, such as whether cryptocurrency investors differ from the rest of the population with respect to their income or education. Additionally, we ask what returns the cryptocurrency investors have achieved and whether they were able to beat the market. Do cryptocurrency investors classify as short-term speculators or do they look towards the long term? The literature on individual stock investors offers a suitable basis and benchmark. Our explorative study extends this literature by analyzing investors, classifying them according to their success and using multivariate analysis to identify factors that influence investment success.

2 Literature and hypotheses

Barber and Odean (2013) point out that financial markets (and therefore also cryptocurrency markets) are subject to an adding-up constraint: Whenever someone buys something, someone else must sell it. Thus, the success of one investor necessitates the failure of another, which makes trading a zero-sum game. If transaction costs, like trading fees, are taken into account, most individual investors underperform the market. The returns achieved by individual stock investors have been estimated at 1.5% below the market index, with underperformance of 6.5% for active investors (Barber and Odean 2000).

H1: *Individual investors underperform in comparison to market returns.*

Yet any aggregate statistics on underperformance mask the huge differences among individual investors. We therefore also investigate whether the investors' socio-demographics affect their success. The literature shows that men generally trade more often than women and achieve lower average returns, while both underperform the market (Barber and Odean 2001). Anderson (2013) finds that various socio-demographic characteristics of individual stock investors affect their investment performance. Lower income, wealth, age and education are associated with less diversified portfolios, higher trading frequency and lower financial performance. However, Korniotis and Kumar (2011) find that investment performance tends to decline with age. According to Grinblatt et al. (2012), stock bought by investors with a high IQ generates high positive returns over investment horizons of up to one month. Similarly, well-educated investors outperform others by up to 3.6% annually (Korniotis and Kumar 2013).

H2: *Socio-demographics, which we operationalize as a) gender, b) age, c) income and d) the level of education affect the financial performance from investing in cryptocurrency.*

Barber and Odean (2013) ask why so many individual investors self-manage their portfolios when they could use cheaper alternatives such as index funds, which moreover achieve higher returns. Various potential explanations for the irrational behavior or underperformance of individual investors have been proposed, including overconfidence and an illusion of control (Barber and Odean 2002), biased self-assessment (M. Glaser and Weber 2007; Graham et al. 2009), sensation-seeking (Grinblatt and Keloharju 2009) or financial inexperience. Individual investors generally have a home bias, i.e. they prefer assets that they are familiar with, ignoring the fact that foreign stocks offer diversification advantages (French and Poterba 1991). Investors who are associated with a certain industry tend to prefer securities from the same industry, despite the resulting lack of diversification (Døskeland and Hvide 2011). A high self-assessment of competence, as elicited for example through questions about investment products or the assessment of opportunities on the market, is associated with higher trading frequency and greater portfolio diversification (Graham et al. 2009).

H3*: Industry knowledge, which we operationalize as a) the level of knowledge about cryptocurrencies, b) the number of different cryptocurrencies known and c) the number of different cryptocurrency exchanges used, affects the returns from investing in cryptocurrency.*

H4: *Self-assessed attitudes in terms of a) the level of trust in cryptocurrencies and b) the importance of ideological reasons to own cryptocurrencies affects the financial performance from investing in cryptocurrency.*

Diversification helps to reduce the risks regarding investment outcomes. However, individual investors often do not diversify their portfolios, holding only a few different assets – four on average, according to Barber and Odean (2000). Goetzmann and Kumar (2008) show that typical portfolio volatility is unnecessarily high because the correlation among the assets held exceeds the value that would result from randomly selected assets. Ivković et al. (2008) find that a lower level of individual investors' portfolio concentration is associated with higher financial performance. Diversification affects the variability of performance, but not average performance. We control for potential effects of diversification by testing if the number of different cryptocurrencies owned or the number of different cryptocurrencies owned divided by the sum of investment leads to relevant effects.

3 Sample and variables

The data used in this study is based on an online survey conducted from February 8 to March 28, 2019, that is representative of the German adult internet-using population in terms of age and gender. Of the 3,846 respondents, 354 (9.2%) reported owning cryptocurrencies. 225 (5.8%) of them, having provided sufficient information on the size and time of their investment and their current portfolio value, constitute the sample for this study. The survey participants were recruited via mail, received no prior indication as to the topic of the survey, and were financially incentivized to answer the questions. For descriptive analyses of the complete sample we refer to (Blockchain Research Lab 2019a, 2019b).

The respondents were asked to indicate the value of their portfolio at the time of the survey and the amount of their total investment in Euro, excluding any subsequent additional investments based on cryptocurrency trading gains. Both numbers were divided by 1,000 to form the variables *portfolio* and *invest*, respectively. The first dependent variable, *return*, is calculated as: (*portfolio – invest*) / *invest*. As *return* is highly skewed and has positive, negative and zero values, we calculate *return (log)* as: log (*return* +1*)* and use this variable instead for the multivariate analysis. Additionally, we categorize the respondents broadly according to their investment success using the dependent dummy variables *positive*, *negative* and *no change*.

Dummy variables are used to indicate the year of the first investment (*2009* to *2019*) – respondents stated the month and year of their first investment. *coins known* refers to the number of coins known to an investor, while *coins owned* represents the number of different cryptocurrencies that an investor owns – the respondents were asked which ones of the 15 cryptocurrencies with the greatest market capitalization are currently in their portfolios. Dummy variables for individual coin possession were also generated for descriptive analysis (for the full list of the 15 cryptocurrencies, see Table 3). The variable *coins / invest* is calculated as *coins owned / invest*. We use its log for the regression models (*coins / invest (log)).*

The respondents were furthermore asked to indicate to what extent they use their cryptocurrency for each of two purposes: *speculation (short-term)* and *investment (long-term)*. Depending on which purpose is assigned greater importance, the respondents are classified as 1) *short-term* and 2) *long-term* investors. Where the two purposes received the same weight, the respondents were classified as 3) *indifferent* investors.

The participants were also asked to assess their knowledge of cryptocurrencies (*crypto knowledge*) on a scale of 0 (no knowledge) to 10. *exchanges* indicates the number of different cryptocurrency exchanges an investor uses. *trust* refers to the investors' assessment, on a scale of 0 to 10, of their trust in cryptocurrencies, while *ideology* captures, on the same scale, the degree to which ideology motivates the investors to own cryptocurrencies.

Finally, we collected data on a number of socio-demographic variables: *Age* (in years); gender (*male*); and monthly *income*, which was recorded in categories, each of which was in turn assigned a value as follows: 'under €500' (0.45); '€500-999' (0.75); '€1,000-1,499' (1.25); '€1,500-1,999' (1.75); '€2,000-2,999' (2.5); '€3,000-4,999' (4); 'over €5,000' (6.5). *education* approximates a respondent's level of education based on their highest educational attainment. The variable assumes the following values: 0 for 'no school leaving certificate'; 1 for 'lower secondary school'; 3 for 'high school'; 3 for 'commercial or trade training'; 4 for 'university degree'; 5 for 'PhD'.

4 Results

4.1 Descriptive results

4.1.1 Investment characteristics and market returns

Table 1 summarizes investment characteristic for the 225 cryptocurrency investors according to the year of their first investment. Each line presents the number of investors who entered the market in a given year, their total investment and the sum of their portfolio values at the time of the survey. Additionally, among each of these groups of investors, we distinguish three types based on their investment horizon.

The returns achieved by the respondents between their first month and year of investment and the end of March, 2019 (when the survey was conducted), are compared to the development of the market return over the same period. Instead of a market index, as done in the stock literature, we use buy-and-hold returns of Bitcoin. The reason for this is that there is no continuous index over the entire period under consideration. Besides, Bitcoin is highly correlated with the price of other cryptocurrencies (Katsiampa 2019). For the years 2009 to 2013, Bitcoin returns are only estimates, as we were unable to identify precise price histories. From 2013 on, we relied on monthly close prices from *coinmarketcap.com*. The last column of Table 1 shows the share of investors who underperformed compared to Bitcoin market returns over the respective period.

The 225 investors invested a total of around €400,000. Today, their portfolios are worth almost €1.6 million. Most investors entered the cryptocurrency market from 2015 onwards and continued to do so at an increasing rate until 2018. If we extrapolate from the 8 investors who first invested in the first three months of 2019, we obtain 24 new investors in 2019, which suggests a declining interest in cryptocurrencies. The amounts invested have remained at a comparatively high level since 2014. An extrapolation for all of 2019 would yield a sum of €90,760, the highest value yet. Based on their self-assessment, 27% of the individuals are classified as short-term investors, 41% have predominantly long-term investment interests, and the remaining 32% are categorized as 'indifferent'.

Table 1. Cryptocurrency investment statistics by year of first investment

Year	Investors		Sum of investments (€)	Sum of portfolio values (€)	Investor classification			Investors returns		Market returns (Bitcoin)	Share of under-performers
	#	%			Short-term	Long-term	Indiff.	Weighted average	Absolute (€)		
2009	2	1%	2,200	6,500	0%	50%	50%	195%	4,300	532,644,307%	100%
2010	5	2%	1,044	1,574	40%	20%	40%	51%	530	6,781,667%	100%
2011	11	5%	23,482	43,338	18%	45%	36%	85%	19,856	39,457%	100%
2012	5	2%	11,700	12,100	20%	20%	60%	3%	400	27,127%	100%
2013	11	5%	11,654	302,913	27%	64%	9%	2,499%	291,259	3,048%	91%
2014	11	5%	59,024	270,767	18%	27%	55%	359%	211,743	825%	73%
2015	22	10%	62,817	103,880	18%	50%	27%	65%	41,063	1,522%	91%
2016	31	14%	42,929	521,029	29%	42%	29%	1,114%	478,100	764%	68%
2017	58	26%	81,027	145,280	33%	41%	26%	79%	64,253	176%	50%
2018	61	27%	80,527	144,130	25%	38%	38%	79%	63,603	162%	20%
2019	8	4%	22,690	44,620	50%	38%	13%	97%	21,930	110%	63%
Σ	225	100%	399,094	1,596,131	27%	41%	32%	300%	1,197,037	4,888,368%	56%

Bitcoin prices from 2009 to 2012 are estimated annual averages (BTC/EUR ≈ 0.000000188 (2009), 0.000014746 (2010), 0.00286 (2011), 0.00369 (2012)); absolute market index returns are based on the sum invested in a particular month and year.

We find that very early investors, i.e. those who first invested in the years 2009 to 2012, have since generated returns of between 195% (2011) and 51% (2013). The highest average relative returns (2,499%) were generated by those who entered the market in 2013. The highest absolute return accrues to those who first invested in 2016 (€478,100; an average of €15,422 per investor). Most of the effect is attributable to two investors, one of whom invested €500 and realized €180,000 (age 38, male, commercial/trade training, income €2,000-€2,999), while the other one invested €5,500 and realized €185,000 (age 38, male, PhD, income above €5,000).

All those who first invested in the years 2009 to 2012 have theoretically underperformed the market. We see the first 'winners' among those who entered in 2013, with 9% of them beating the market. This share rose to 27% among those who first invested in 2014. The years of market entry that produced the highest shares of 'winners' are 2017 (50%) and 2018 (80%). Clearly the market index – as we define it – is hard to beat, considering that a Bitcoin investment of €100 in 2009 would have yielded €531 million by the time of the survey. Of the 225 investors, 99 (44%) beat the market. 25 of them (25%) can be classified as short-term investors and 46 (46%) as long-term investors, the rest being indifferent. With hindsight, those long-term investors clearly had the superior strategy, considering the high buy-and-hold returns in the market.

4.1.2 Sample statistics and differences across investment outcomes

The average investment amounted to €1,772, which corresponds to 60.5% of the investors' average monthly disposable income of approximately €2,930. The average final portfolio value is €7,094 – a return of 300%. The average portfolio contains just over two of the top 15 cryptocurrencies in terms of market capitalization. Group III, i.e. those investors who achieved positive returns, has the lowest average investment (€1,445) and the highest average portfolio value (€11,172), which corresponds to a 673% increase in value.

The 225 investors are familiar with 5.92 of the top 15 cryptocurrencies on average. They rated their knowledge about cryptocurrencies at an average of 7.58, with a comparatively small standard deviation of 1.79 (cf. Table A2). The members of group III know the largest number of cryptocurrencies (6.17), owning 2.09 of them, while group IV investors (negative returns) know only 6 cryptocurrencies. The difference in the number of known cryptocurrencies between the groups is significant at the 5%-level. Group III investors consider themselves most knowledgeable about cryptocurrencies (average self-assessment of 7.84), the difference to the less successful investors (average of 7.25) again being significant.

Across the whole sample, the level of trust in cryptocurrencies was rated at an average of 6.79, and a value of 6.16 was given for the ideological motivation to own cryptocurrencies. Regarding the level of trust, groups II and III are very similar, while the value in group IV is markedly lower. The difference between groups III and IV is significant at the 5%-level. A similar patter exists with respect to the level of ideology: Groups II and III are close to each other but the difference between those with positive and negative returns is significant at the 1%-level. It is conceivable that the investment success of group III caused its members to place greater trust in cryptocurrency and to ascribe their investment to ideology.

Table 2. Sample statistics and differences across sub-samples

	I. Full sample	II. No change	III. Positive returns	IV. Negative returns	Δ III. vs. IV
Investment					
Invest	1.77	1.78	1.45	2.59	1.15
Portfolio	7.09	1.78	11.17	1.50	9.67**
Industry knowledge					
Crypto knowledge	7.58	7.26	7.84	7.25	0.60**
Coins known	5.92	4.85	6.17	6.00	0.17**
Exchanges	1.88	1.21	2.13	1.75	0.37
Attitudes					
Trust	6.79	7.00	7.01	6.26	0.75**
Ideology	6.16	6.44	6.46	5.42	1.04***
Demographics					
Age	37.64	38.82	37.21	37.83	0.62
Male	0.77	0.71	0.77	0.82	0.05
Income	2.93	2.74	3.13	2.64	0.48**
Education	3.01	2.82	3.06	3.02	0.05
Diversification					
Coins owned	2.02	2.09	2.08	2.07	0.01
Coins / invest	0.03	0.03	0.06	0.03	0.03
Observations	225	34	126	65	
% of full sample (n=3,846)	5.82%	0.87%	3.26%	1.69%	
% of crypto investors (n=225)	100%	15%	56%	29%	

***,**, * indicates significance at the 1%, 5% and 10% level, respectively (t-test).

Cryptocurrency investors are predominantly male (77%), 37.6 years old on average, have a monthly income of €2,930 and an average education score of 3.01. The age distribution across the three outcome groups is quite similar, with group II showing the highest average age at 38.82 and group III the lowest at 37.21. The proportion of male investors is highest in the group with negative returns and lowest in the group with positive returns, although the difference is insignificant. In terms of income, however, the difference of €1,040 between groups III (€3,130) and II (€2,640) is significant at the 5% level. Further statistics on subdivisions of the age, income and education metrics can be found in Table A1. We identify is a highly significant difference of 16% in the €1,000 to €1,499 pay grade between individuals with positive (9%) and negative (25%) returns.

4.1.3 Individual possession of different cryptocurrencies

While the previous sections have dealt only with cryptocurrencies in general, we now turn to individual currencies. Table 3 shows how popular the 15 largest cryptocurrencies are within the sample and the outcome groups. The selection of the top 15 cryptocurrencies was based on market capitalization (on coinmarketcap.com). The respondents also had the opportunity to name any other coins they owned beyond those 15. Ten other currencies were mentioned, of which only Dogecoin (DOGE) was mentioned more than once.

Table 3. Possession of the 15 'biggest' cryptocurrencies among the sample and outcome groups

	I. Full sample	II. No change	III. Positive returns	IV. Negative returns	Δ III. vs. IV.
Bitcoin (BTC)	81.78%	70.59%	86.51%	78.46%	8.05%
Ethereum (ETH)	29.33%	23.53%	28.57%	33.85%	5.27%
Ripple (XRP)	20.00%	14.71%	20.63%	21.54%	0.90%
Bitcoin Cash (BCH)	13.78%	11.76%	16.67%	9.23%	7.44%
EOS (EOS)	3.11%	5.88%	3.17%	1.54%	1.64%
Stellar Lumens (XLM)	3.56%	5.88%	2.38%	4.62%	2.23%
Litecoin (LTC)	15.11%	11.76%	15.08%	16.92%	1.84%
Tether (USDT)	3.11%	2.94%	1.59%	6.15%	4.57%*
Bitcoin SV (BSV)	2.67%	5.88%	1.59%	3.08%	1.49%
TRON (TRX)	7.11%	5.88%	7.14%	7.69%	0.55%
Cardano (ADA)	1.78%	0.00%	1.59%	3.08%	1.49%
Iota (IOT)	7.11%	0.00%	8.73%	7.69%	1.04%
Monero (XMR)	6.22%	8.82%	5.56%	6.15%	0.60%
Binance Coin (BNB)	2.22%	0.00%	2.38%	3.08%	0.70%
Dash (DSH)	5.33%	0.00%	7.14%	4.62%	2.53%
Observations	225	34	126	65	

* indicates significance at the 10% level (t-test).

The cryptocurrencies are ordered by their market capitalization. The largest currencies globally are also the ones which are most widely held by the investors in our sample: Bitcoin (81.78%), Ethereum (29.33%) and Ripple (20%). Litecoin (15.11%) is the fourth most popular currency in the sample and ranks in seventh place based on market capitalization. Cardano (1.78%) and Binance Coin (2.22%) are the least popular choices among the top 15 assets. EOS (3.11%) and Stellar Lumens (3.56%) are likewise not very common in the sample despite being the fifth- and sixth-largest cryptocurrencies, respectively. Iota, which ranks 12th in terms of global market capitalization, has its legal entity based in Germany. This may explain its comparatively large prevalence in the sample (7.11%).

The popularity of the individual assets varies considerably across the three outcome groups, though the difference between groups III and IV is significant only in the case of Tether ($\Delta = 4.57\%$; $p<.1$). Tether (USDT) is a so-called stable coin, which is covered by dollars in a conventional bank account, so the value of the USDT is 1:1 tied to the USD. Tether is a kind of digital dollar that can be exchanged back into conventional currency if necessary. The price of Tether is therefore much less volatile than that of the other assets, which are not backed by any financial assets. One explanation for this may be that investors have switched to Tether at comparatively unfavorable times. The stable coin Tether has only been occupying a relevant position in the market since 2017.

At 86.51%, Bitcoin is most prevalent in group III. The prevalence rate is lower by 8% in group IV and by 16% in group II. By contrast, both the second and the third most popular currencies are more prevalent in group IV than in group III. Significant differences also exist for Bitcoin Cash. At 16.67%, the prevalence is 7.44% percentage points higher in group III than in group IV. There is some connection with the distribution of Bitcoin across the groups as Bitcoin Cash is a hard fork: Every Bitcoin owner also received Bitcoin Cash in July 2017. On the other hand, the prevalence of Bitcoin SV, which is in turn a hard fork of Bitcoin Cash that was distributed in November 2018, is almost twice as high in group IV (3.08%) as in group III ($\Delta = 1.49$).

5 Multivariate results

Table A2 shows descriptive statistics, correlations between the variables and variance inflation factors (VIFs). Not surprisingly, the number of cryptocurrencies known correlates with the number of currencies owned (0.45; $p<.05$). The more cryptocurrencies an investor owns, the more exchanges they are likely to use ($r=0.58$; $p<.05$). Further significant correlations are observed between the level of trust in cryptocurrency and the importance of ideology for owning cryptocurrency ($r=0.46$; $p<.05$), and between knowledge about and trust in cryptocurrencies ($r=0.5$; $p<.05$).

Table 4 presents the results of two regression models for each of the three dependent variables *return (log)*, *positive*, and *negative*. Coefficients and heteroscedasticity-robust standard errors (in brackets) are shown. For each of the dependent variables we test two models: In the first model, we check for possible diversification effects by introducing the variable *coins owned* and in the second model using the variable *coins / invest (log)*. *Coins owned* also serves as a control variable to take into account any effects of an s-shaped utility curve (Kahneman and Tversky 1979). All models incorporate year dummies.

Table 4. Regression results to predict investment outcomes

Model	I.	II.	III.	IV.	V.	VI.
Dependent variable	Return (log)	Return (log)	Positive	Positive	Negative	Negative
	Coeff. (SE)	Coeff. (SE)	Coeff. (SE)	Coeff. (SE)	Coeff. (SE)	Coeff. (SE)
Industry knowledge						
Crypto knowledge	0.081 (0.046) *	0.088 (0.046) *	0.150 (0.099)	0.159 (0.102)	-0.096 (0.100)	-0.124 (0.103)
Coins known	-0.034 (0.022)	-0.026 (0.023)	0.035 (0.049)	0.024 (0.047)	0.008 (0.053)	0.014 (0.051)
Exchanges	-0.055 (0.055)	-0.039 (0.035)	0.077 (0.113)	0.015 (0.115)	0.053 (0.104)	0.111 (0.092)
Attitudes						
Trust	0.023 (0.040)	0.015 (0.040)	-0.060 (0.086)	-0.064 (0.087)	-0.024 (0.092)	-0.007 (0.090)
Ideology	0.007 (0.032)	0.018 (0.031)	0.061 (0.062)	0.068 (0.063)	-0.141 (0.068) **	-0.167 (0.067) **
Demographics						
Age	0.006 (0.006)	0.008 (0.006)	-0.000 (0.010)	-0.001 (0.010)	-0.007 (0.011)	-0.007 (0.012)
Male	-0.062 (0.161)	0.013 (0.159)	-0.143 (0.369)	0.050 (0.381)	0.535 (0.403)	0.395 (0.413)
Income	0.071 (0.055)	0.118 (0.053) **	0.130 (0.104)	0.152 (0.109)	-0.173 (0.113)	-0.250 (0.121) **
Education	-0.074 (0.064)	-0.030 (0.059)	-0.026 (0.149)	-0.008 (0.084)	0.090 (0.171)	0.034 (0.174)
Diversification						
Coins owned	0.069 (0.065)	-	-0.121 (0.120)	-	0.069 (0.122)	-
Coins / invest (log)	-	0.159 (0.037) ***	-	0.098 (0.084)	-	-0.255 (0.089) ***
Observations	220	216	220	216	220	216
Adj. R2 (pseudo R2)	0.16	0.22	0.28	0.34	0.40	0.34
Estimation technique	OLS	OLS	Logistic	Logistic	Logistic	Logistic

***, **, * indicates significance at the 1%, 5% and 10% level, respectively; constant term and year dummies included but not shown.

The model for *return (log)* is estimated by OLS, those for the binary dependent variables by logistic regression. Models predicting negative investment outcome (V and VI) have the explanatory power, with pseudo R^2 values of 0.34 and 0.40, followed by models III and IV (positive outcomes), with pseudo R^2 of 0.28 and 0.34. Models I and II, with adjusted R^2 between 0.16 and 0.22, have the lowest predictive power.

The effects we identify are largely consistent across the three outcome variables, though the level of significance varies. Models I and II show 10%-significant positive effects of *crypto knowledge* on returns. We also identify significant positive effects for *income* ($p<.05$) and *coins / invest (log)* ($p<.01$) in model II. In model III and IV that predict positive financial performance, none of the variables have a significant effect. For models V and VI, which predict negative financial performance, we find significant negative effects of *income* ($p<.05$) and *coins / invest (log)* ($p<.01$) in model VI. The effect of *ideology* is significantly negative in both models that predict negative outcome.

6 Discussion

This study aims to provide a scientific basis for the analysis of cryptocurrency investors, their behavior and outcomes. Investors are typically male (77%), 38 years old on average (note that only adults were surveyed) and have an above-average monthly net income of about €2,930. A reason for the identified high share of males can possibly be explained by sex-related differences in technology-oriented fields or that males generally follow higher-risk strategies (Powell and Ansic 1997).

We identify a number of relevant factors that affect the distribution of returns. Most investors achieved positive returns, but less than half (44%) beat our market index based on Bitcoin returns. We are therefore able to confirm hypothesis H1: Similar to individual investments in stocks (Barber and Odean 2000, 2001), the average cryptocurrency investor underperforms the market. In this sense, cryptocurrencies resemble other financial assets. However, it should be noted that the hypothetical buy-and-hold yields of an early investment in Bitcoin are so extremely high that investors have a very hard time beating this ‘market’ index.

Our analysis of the socio-economic indicators yields mixed results. The hypotheses regarding gender (H2a), age (H2b) and education (H2d) fail to find empirical support. We do however find a significant positive effect of *income* on returns from investing in cryptocurrencies, confirming hypothesis H2c. This finding is in line to the literature on individual investments into stocks, where lower income is associated with lower returns (Korniotis and Kumar 2011).

Individuals who know more about cryptocurrency achieve better results, as evidenced by the significant influence of *crypto knowledge* (confirming hypothesis H3a). In this respect, the results may indicate that time invested in knowledge about the asset class is crucial for financial performance. Most of the high returns of (early) investors are likely attributable simply to overall market growth. In many cases, pure luck or even technical inability to sell the cryptocurrency will have led to extremely positive returns. This may explain why, in contrast to the stock market literature (Grinblatt et al. 2012; Korniotis and Kumar 2011, 2013), the level of education appears to have no effect.

Industry knowledge in the form of a fundamental understanding of cryptocurrency promotes financial performance. However, it should be noted that this knowledge is self-assessed by the respondents. There may be a causal connection here. The occurrence of positive financial returns may only lead to people building up a significantly higher knowledge of cryptocurrencies. It is also conceivable that successful investors tend to (unconsciously) overstate their knowledge, and vice versa. The other two industry knowledge variables do not produce any significant effects, so we reject hypotheses H3b and H3c.

The descriptive statistics show significant differences regarding the attitudes of investors between the positive and negative return groups, whereas in the regressions, this is only the case for the level of ideology with respect to one of the dependent variables (negative outcome). In this respect, we basically reject hypotheses H4a and H4b. We note that any effects of ideology only appear to apply to negative financial performance, and we caution that the self-assessed variables may be subject to reverse causation: An unsuccessful investor may place less trust in cryptocurrencies or less importance on ideology.

On average, investors hold about two cryptocurrencies in their portfolio – fewer than the average of four stocks identified by Barber and Odean (2000). We fail to identify any significant effects of portfolio concentration or diversification in terms of coins owned but find highly significant effects of the ratio between coins owned and the sum of investments, which measures diversification as a function of the amount invested. The results are in line with some of the existing literature (e.g. Ivković et al. 2008). Our lack of effects in the respect of total coins owned may perhaps be explained by the a high correlation between cryptocurrencies (Katsiampa 2017), which renders diversification less relevant. This consideration may be supported by the ownership ratios of individual cryptocurrencies (cf. Table 3).

The sum of investments of the cryptocurrency owners we surveyed average €1,773 or around 60% of the respondents' monthly income. Thus, most German retail investors do not appear to take excessive financial and social risks when buying cryptocurrency, since even a total loss of the investment would not threaten their existence. The comparatively low stakes may indicate a general awareness that crypto assets entail serious risk. At least from the standpoint of consumer protection, regulation of the industry thus does not seem imperative. This conclusion does not apply, however, to crime that occurs within the cryptocurrency industry due to anonymity and irreversible transactions (Ante 2018, 2019; Feng et al. 2018).

6.1 Limitations and future research

Various limitations of this study result from the available survey data. Most importantly, a sample of 225 investors is comparatively small, despite being based on a nationally representative data set of over 3,800 persons. Consequently, the results may be unduly distorted by individual outliers. They should therefore be interpreted with care and require substantiation by follow-up research. All surveys suffer from the limitation that not everyone tells the truth. For example, very successful investors may not want to disclose their returns in order to protect their identity or, at the opposite end of the spectrum, 'losers' may hesitate to come out as such – even though the responses are anonymous. Actual stock exchange data could yield more accurate results but do not appear to be available at present.

The survey asks about the total amount invested in cryptocurrencies on the one hand and about the year of the first investment in cryptocurrency on the other hand. This suggests that the results presented in Table 1 should be critically scrutinized, since it is assumed that all investments were made at the time of the initial investment in order to calculate performance against the market. Future research should check the results based on a different data basis. The use of Bitcoin returns may be subject to survivorship bias.

The questionnaire only lists the 15 largest currencies, yet four respondents additionally owned Dogecoin. It is conceivable that the ownership ratio would be higher if Dogecoin had also been included in the list due to a selection bias.

Our distinction between 'short-term speculators' and 'long-term investors' according to the respondents' investment horizon (see Table 1) provides only limited basis for further analysis. Future research should therefore investigate long-horizon versus short-horizon investment motivations and outcomes. The literature on individual stock investors provides a suitable basis for such an endeavor

(Barber and Odean 2000, 2013). Corbet, Meegan, et al. (2018) find that investors with a short investment horizon may gain diversification benefits by investing in multiple cryptocurrencies.

The literature on individual stock investors examines their trading behavior on the basis of the amount and profitability of individuals' trades. It examines what types of trades (limit vs. market orders) investors use and to what extent fees influence individual performance. Kelley and Tetlock (2013) find positive short-term returns for both order types, while Linnainmaa (2010) identifies negative performance for limit orders and positive performance for market orders. These results differ in Barber et al. (2009), where only limit orders yield positive short-term returns. Since cryptocurrency markets resemble traditional stock markets in some respects but are quite different in others (e.g. 24/7 trading; decentralized trading venues etc.), it would be interesting to replicate this type of analysis for cryptocurrency markets.

Cryptocurrency markets are extensively discussed in online and social media. There is a considerable amount of disinformation, since for example various news outlets sell articles or influencers on social media channels like Twitter advertise specific cryptocurrencies. The low level of regulation means that there are much larger grey areas to exploit than in traditional markets. Promising research topic include the analysis of media influence or disinformation, social media sentiment and returns (Giannini et al. 2018), and social trading (Dorfleitner et al. 2018; Jin et al. 2019). The topic of social recognition of investment decisions that may result in increased individual trading (Mensmann and Breitmayer 2018) can be tested for cryptocurrency markets.

7 Conclusion

This paper has analyzed the financial performance and socio-demographic characteristics of cryptocurrency investors on the basis of an online survey that is representative of the German adult internet-using population. The 225 individual investors we examined have generated an average return of 300% over periods between one and ten years. However, similarly to other financial markets, fewer than half of them (44%) were able to outperform the market. Based on their investment horizon, we categorized 44% of the respondents as long-term investors and 27% as short-term investors. 77% of the cryptocurrency investors are male, and they are 38 years old on average.

While we find that self-assessed knowledge about cryptocurrencies tends to promote larger returns from cryptocurrency investments, the level of formal education has no significant effect. We therefore suspect that the former effect is in fact attributable to reverse causation: Cryptocurrency investment success breeds confidence in one's own abilities, leading to greater self-ascribed knowledge in the field, rather than other way around. Another interesting finding relates to the market dominance of Bitcoin, which is owned by 82% of the investors, well ahead of Ethereum (29%). This accords with our finding that the average investor owns no more than two different cryptocurrencies.

Our results provide a first scientific consideration of individual investors in cryptocurrencies and may be used as a basis for a variety of future investigations. Investors seem to be aware of the risk associated with cryptocurrencies, as evidenced by the fact that they invested only 60% of their monthly net income – a survivable amount, even in the event of a total loss. In this respect, our study may contribute to the ongoing debate about the risk and regulation of cryptocurrencies.

References

Al Shehhi, A., Oudah, M., & Aung, Z. (2014). Investigating Factors behind Choosing a Cryptocurrency. In *IEEE international conference on industrial engineering and engineering management*.

Anderson, A. (2013). Trading and under-diversification. *Review of Finance*, *17*(5), 1699–1741. doi:10.1093/rof/rfs044

Ante, L. (2018). Cryptocurrency, Blockchain and Crime. In K. McCarthy (Ed.), *The Money Laundering Market: Regulating the Criminal Economy* (pp. 171–198). Agenda Publishing. doi:10.2307/j.ctv5cg8z1.10

Ante, L. (2019). *Market Reaction to Exchange Listings of Cryptocurrencies*. doi:10.13140/RG.2.2.19924.76161

Ante, L., & Fiedler, I. (2019). Cheap Signals in Security Token Offerings (STOs). doi:10.2139/ssrn.3356303

Ante, L., Sandner, P., & Fiedler, I. (2018). Blockchain-Based ICOs: Pure Hype or the Dawn of a New Era of Startup Financing? *Journal of Risk and Financial Management*, *11*(4), 80. doi:10.3390/jrfm11040080

Barber, B. M., Lee, Y. T., Liu, Y. J., & Odean, T. (2009). Just how much do individual investors lose by trading? *Review of Financial Studies*, *22*(2), 609–632. doi:10.1093/rfs/hhn046

Barber, B. M., & Odean, T. (2000). Trading is hazardous to your wealth: The common stock investment performance of individual investors. *Journal of Finance*, *55*(2), 773–806. doi:10.1111/0022-1082.00226

Barber, B. M., & Odean, T. (2001). Boys will be boys: Gender, overconfidence, and common stock investment. *Quarterly Journal of Economics*, *116*(1), 261–292. doi:10.1162/003355301556400

Barber, B. M., & Odean, T. (2002). Online Investors: Do the Slow Die First? *Review of Financial Studies*, *15*(2), 455–487. doi:10.1093/rfs/15.2.455

Barber, B. M., & Odean, T. (2013). The Behavior of Individual Investors. In *Handbook of the Economics of Finance* (Vol. 2, pp. 1533–1570). Elsevier B.V. doi:10.1016/B978-0-44-459406-8.00022-6

Baur, D. G., Hong, K. H., & Lee, A. D. (2018). Bitcoin: Medium of exchange or speculative assets? *Journal of International Financial Markets, Institutions and Money*, *54*, 177–189. doi:10.1016/j.intfin.2017.12.004

Blockchain Research Lab. (2019a). *Perceived and Actual Use of Cryptocurrencies Results of a representative survey among German Internet users*. https://www.blockchainresearchlab.org/wp-content/uploads/2019/07/Report-2-Perceived-and-actual-use-of-cryptocurrencies-1.pdf

Blockchain Research Lab. (2019b). *The State of Cryptocurrency Adoption : Results of a representative survey among German Internet users*. https://www.blockchainresearchlab.org/wp-content/uploads/2019/07/The_State_of_Cryptocurrency_Adoption_Q1_2019_Germany_Blockchain_Research_Lab.pdf

Cheah, E. T., & Fry, J. (2015). Speculative bubbles in Bitcoin markets? An empirical investigation into the fundamental value of Bitcoin. *Economics Letters*, *130*, 32–36. doi:10.1016/j.econlet.2015.02.029

Corbet, S., Lucey, B., & Yarovaya, L. (2018). Datestamping the Bitcoin and Ethereum bubbles. *Finance Research Letters*, *26*, 81–88. doi:10.1016/j.frl.2017.12.006

Corbet, S., Meegan, A., Larkin, C., Lucey, B., & Yarovaya, L. (2018). Exploring the dynamic relationships between cryptocurrencies and other financial assets. *Economics Letters*, *165*, 28–34. doi:10.1016/j.econlet.2018.01.004

Dorfleitner, G., Fischer, L., Lung, C., Willmertinger, P., Stang, N., & Dietrich, N. (2018). To follow or not to follow – An empirical analysis of the returns of actors on social trading platforms. *Quarterly Review of Economics and Finance*, *70*, 160–171. doi:10.1016/j.qref.2018.04.009

Døskeland, T. M., & Hvide, H. K. (2011). Do Individual Investors Have Asymmetric Information Based on Work Experience? *Journal of Finance*, *66*(3), 1011–1041. doi:10.1111/j.1540-6261.2011.01658.x

Dyhrberg, A. H. (2016). Bitcoin, gold and the dollar – A GARCH volatility analysis. *Finance Research Letters*, *16*, 85–92. doi:10.1016/j.frl.2015.10.008

Dyhrberg, A. H., Foley, S., & Svec, J. (2018). How investible is Bitcoin? Analyzing the liquidity and transaction costs of Bitcoin markets. *Economics Letters*, *171*, 140–143. doi:10.1016/j.econlet.2018.07.032

Fahlenbrach, R., & Frattaroli, M. (2019). *ICO Investors*. doi:10.2139/ssrn.3419944

Feng, W., Wang, Y., & Zhang, Z. (2018). Informed trading in the Bitcoin market. *Finance Research Letters*, *26*, 63–70. doi:10.1016/j.frl.2017.11.009

Fisch, C., Masiak, C., Vismara, S., & Block, J. (2019). Motives and profiles of ICO investors. *Journal of Business Research*. doi:10.1016/j.jbusres.2019.07.036

French, K., & Poterba, J. (1991). Investor Diversification and International Equity Markets. *The American Economic Review*. doi:10.2307/2006858

Giannini, R., Irvine, P., & Shu, T. (2018). Nonlocal Disadvantage: An Examination of Social Media Sentiment. *The Review of Asset Pricing Studies*, *8*(2), 293–336. doi:10.1093/rapstu/rax020

Gibbs, T., & Yordchim, S. (2014). Thai Perception on Litecoin Value. *International Journal of Social, Education,* *Economics and Management Engineering*, *8*(8), 2589–2591.

Glaser, F., Zimmermann, K., Haferkorn, M., Weber, M. C., & Siering, M. (2014). *Bitcoin - asset or currency? revealing users' hidden intentions*. https://ssrn.com/abstract=2425247

Glaser, M., & Weber, M. (2007). Overconfidence and trading volume. *Geneva Risk and Insurance Review*, *32*(1), 1–36. doi:10.1007/s10713-007-0003-3

Goetzmann, W. N., & Kumar, A. (2008). Equity portfolio diversification. *Review of Finance*, *12*(3), 433–463. doi:10.1093/rof/rfn005

Graham, J. R., Harvey, C. R., & Huang, H. (2009). Investor competence, trading frequency, and home bias. *Management Science*, *55*(7), 1094–1106. doi:10.1287/mnsc.1090.1009

Grinblatt, M., & Keloharju, M. (2009). Sensation seeking, overconfidence, and trading activity. *Journal of Finance*, *64*(2), 549–578. doi:10.1111/j.1540-6261.2009.01443.x

Grinblatt, M., Keloharju, M., & Linnainmaa, J. T. (2012). IQ, trading behavior, and performance. *Journal of Financial Economics*, *104*(2), 339–362. doi:10.1016/j.jfineco.2011.05.016

Hur, Y., Jeon, S., & Yoo, B. (2015). *Is Bitcoin a Viable E-Business?: Empirical Analysis of the Digital Currency's Speculative Nature*.

Ivković, Z., Sialm, C., & Weisbenner, S. (2008). Portfolio concentration and the performance of individual investors. *Journal of Financial and Quantitative Analysis*, *43*(3), 613–655. doi:10.1017/S0022109000004233

Jin, X., Zhu, Y., & Huang, Y. S. (2019). Losing by learning? A study of social trading platform. *Finance Research Letters*, *28*(April 2018), 171–179. doi:10.1016/j.frl.2018.04.017

Kahneman, D., & Tversky, A. (1979). Prospect Theory: An Analysis of Decision under Risk. *Econometrica*, *47*(2), 263–292. doi:10.2307/1914185

Katsiampa, P. (2017). Volatility estimation for Bitcoin: A comparison of GARCH models. *Economics Letters*, *158*, 3–6. doi:10.1016/j.econlet.2017.06.023

Katsiampa, P. (2019). Volatility co-movement between Bitcoin and Ether. *Finance Research Letters*, *30*, 221–227. doi:10.1016/j.frl.2018.10.005

Kelley, E. K., & Tetlock, P. C. (2013). How Wise Are Crowds? Insights from Retail Orders and Stock Returns. *Journal of Finance*, *68*(3), 1229–1265. doi:10.1111/jofi.12028

Korniotis, G. M., & Kumar, A. (2011). Do older investors make better investment decisions? *Review of Economics and Statistics*, *93*(1), 244–265. doi:10.1162/REST_a_00053

Korniotis, G. M., & Kumar, A. (2013). Do portfolio distortions reflect superior information or psychological biases? *Journal of Financial and Quantitative Analysis*, *48*(1), 1–45. doi:10.1017/S0022109012000610

Kristoufek, L. (2018). On Bitcoin markets (in)efficiency and its evolution. *Physica A: Statistical Mechanics and its Applications*, *503*, 257–262. doi:10.1016/j.physa.2018.02.161

Linnainmaa, J. T. (2010). Do limit orders alter inferences about investor performance and behavior? *Journal of Finance*, *65*(4), 1473–1506. doi:10.1111/j.1540-6261.2010.01576.x

Mensmann, B., & Breitmayer, B. (2018). Social recognition and investor overcondence. doi:10.2139/ssrn.3140827

Mills, D. J., & Nower, L. (2019). Preliminary findings on cryptocurrency trading among regular gamblers: A new risk for problem gambling? *Addictive Behaviors*, *92*, 136–140. doi:10.1016/j.addbeh.2019.01.005

Nakamoto, S. (2008). Bitcoin: A Peer-to Peer Electronic Cash System. https://bitcoin.org/bitcoin.pdf. Accessed 12 June 2019

Powell, M., & Ansic, D. (1997). Gender differences in risk behaviour in financial decision-making: An experimental analysis. *Journal of Economic Psychology*, 605–628. doi:10.1016/S0167-4870(97)00026-3

Schuh, S., & Shy, O. (2016). US consumers' adoption and use of Bitcoin and other virtual currencies. In *DeNederlandsche bank: Retail payments: mapping out the road ahead.*

Yermack, D. (2015). Is Bitcoin a Real Currency? *Handbook of digital currency*. doi:10.2139/ssrn.2361599

Appendix

Table A1. Sample statistics and differences across sub-samples for demographics

	I.	II.	III.	IV.	Δ
	Full sample	No change	Positive returns	Negative returns	III. vs. IV.
Age groups					
18-24 years	0.17	0.12	0.17	0.20	0.03
25-34 years	0.29	0.35	0.31	0.23	0.08
35-49 years	0.34	0.35	0.32	0.37	0.05
50+ years	0.20	0.18	0.20	0.20	0.00
Income groups					
Under €500	0.02	0.03	0.02	0.02	0.00
€500 to €999	0.04	0.09	0.02	0.05	0.03
€1,000 to €1,499	0.13	0.09	0.09	0.25	0.16***
€1,500 to €1,999	0.17	0.21	0.15	0.18	0.03
€2,000 to €2,999	0.22	0.21	0.26	0.15	0.11*
€3,000 to €4,999	0.32	0.32	0.36	0.26	0.10
Over €5,000	0.08	0.06	0.10	0.08	0.02
Education levels					
No school leaving certificate	0.01	0.03	0.00	0.02	0.02
Lower secondary school	0.09	0.12	0.10	0.06	0.04
High school	0.20	0.18	0.20	0.20	0.00
Commercial training	0.12	0.21	0.11	0.09	0.01
Trade training	0.21	0.18	0.19	0.26	0.07
University degree	0.34	0.26	0.38	0.35	0.03
PhD	0.04	0.03	0.05	0.02	0.03
Observations	225	34	126	65	

***, * indicates significance at the 1% and 10% level, respectively (t-test).

Table A2. Descriptive statistics, correlations and variance inflation factors

Variables		N	Mean	SD	p50	Min	Max	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(17)	(18)	VIF
Dependent variables																						
(1)	Return (log)	225	1.23	1.05	0.85	0.01	6.50	1.00														1.81
(2)	Positive	225	0.56	-	1	0	1	**0.63**	1.00													2.32
(3)	Negative	225	0.29	-	0	0	1	**-0.52**	**-0.72**	1.00												2.30
Industry knowledge																						
(4)	Crypto knowledge	225	7.58	1.79	8	1	10	**0.16**	**0.16**	-0.12	1.00											1.73
(5)	Coins known	225	5.92	3.48	5	1	15	-0.01	0.08	0.01	**0.22**	1.00										1.40
(6)	Exchanges	225	1.88	2.14	1	0	19	0.07	0.13	-0.04	**0.23**	**0.28**	1.00									1.83
Attitudes																						
(7)	Trust	225	6.79	2.11	7	0	10	**0.15**	0.12	**-0.16**	**0.50**	0.12	**0.25**	1.00								1.45
(8)	Ideology	225	6.16	2.65	7	0	10	0.10	0.13	**-0.18**	**0.32**	0.03	**0.31**	**0.46**	1.00							2.14
Demographics																						
(9)	Age	225	37.64	13.80	35	18	85	0.03	-0.03	0.01	-0.07	-0.13	**-0.15**	**-0.22**	-0.21	1.00						1.17
(10)	Male	225	0.77	-	1	0	1	-0.02	-0.01	0.06	**0.16**	0.08	-0.11	-0.02	0.00	0.03	1.00					1.16
(11)	Income	223	2.93	1.56	2.50	0.45	6.5	0.12	**0.14**	-0.12	**0.27**	**0.17**	**0.22**	**0.15**	0.13	0.02	0.09	1.00				1.27
(12)	Education	225	3.01	1.06	3	0	5	0.03	0.05	0.00	**0.20**	0.12	0.01	0.00	-0.01	0.05	0.19	0.34	1.00			1.27
Diversification																						
(18)	Coins owned	225	2.02	1.67	1	0	15	0.07	0.04	0.02	**0.19**	**0.45**	**0.58**	**0.15**	0.15	-0.18	-0.06	0.13	0.07	1.00		2.16
(19)	Coins / invest (log)	221	-5.39	1.96	-5.52	-10.82	0.41	**0.17**	0.01	-0.08	**-0.14**	-0.05	0.02	-0.02	-0.09	-0.04	-0.24	-0.29	-0.23	0.10	1.00	1.28

Correlations that are significant at the 5%-level are highlighted in bold.

Declarations

Availability of data and materials

The datasets used and/or analyzed during the current study are available from the corresponding author on request.

Conflicts of interest

Not applicable.

Funding

Not applicable.

Acknowledgements

Not applicable.

About the Blockchain Research Lab

The Blockchain Research Lab promotes independent science and research on blockchain technologies and the publication of the results in the form of scientific papers and contributions to conferences and other media. The BRL is a non-profit organization aiming, on the one hand, to further the general understanding of the blockchain technology and, on the other hand, to analyze the resulting challenges and opportunities as well as their socio-economic consequences.

www.blockchainresearchlab.org

Blockchain Research Lab