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Abstract

We investigate the demographic characteristics, trading patterns, and performance of 465.926 brokerage accounts with respect to cryptocurrency trading. We find that cryptocurrency trading became increasingly popular across individuals of all different groups of age, gender, and trading patterns. Yet, men are more likely to engage in cryptocurrency trading, trade more frequently, and more speculative, respectively. As a result, men realize lower returns. Furthermore, we find that investors vary their trading patterns across different asset classes.

Keywords: cryptocurrencies, bitcoin, trading, investor returns, demographics

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JEL Classification: G11, G40.

1. Introduction

Recently, cryptocurrencies have been subject to much societal attention and experienced large fluctuations in their exchange rates (Urquhart, 2018). Researchers have reported anomalies in cryptocurrency returns (Urquhart, 2016, 2017), characteristics of pricing bubbles (Cheung et al., 2015.; Corbet et al., 2018), and significantly higher average volatility compared to other asset classes (Dwyer, 2015). Without a fundamental value, the existence and price of a cryptocurrency is legitimized and determined by public attention and the trust of its investors (Cheah & Fry, 2015). Yet, little is known about who trades cryptocurrencies.

Studies on risk-taking, trading activity, and performance have provided empirical evidence that investors with different demographic characteristics systematically vary with respect to their decision-making in financial markets and that this, in turn, has implications for market dynamics and returns (see, e.g., Barsky et al., 1997; Barber & Odean, 2001; Dorn & Sengmueller, 2009; Eckel & Füllbrunn, 2015). For instance, men and young investors have been found to trade more actively and riskier (Barber and Odean 2001) and male-dominated markets have a higher tendency to exhibit pricing bubbles than markets with a high rate of female investors (Eckel & Füllbrunn, 2015). Therefore, to study the increasing popularity of cryptocurrencies across investors with different demographic characteristics and trading patterns may help to get a better understanding of the market dynamics and price movements of cryptocurrencies. This is important for several reasons. First, knowledge about the market dynamics may help policy makers to effectively regulate cryptocurrencies in order to prevent speculation and pricing bubbles. Second, price movements affect asset values and profits of corporations such as *Microsoft*, *Overstock*, and *PayPal*, which have introduced cryptocurrencies as a valid payment method. Third, returns on cryptocurrencies also affect portfolio values of investors who hold such positions. Finally, with temporary high attention and trading activity, brokerage services may be able to utilize knowledge about cryptocurrency traders to increase their transaction fee income.

We aim to answer the questions of (i) who trades cryptocurrencies, (ii) how they trade them, and (iii) how these investors perform. We investigate a sample of 465.926 individual accounts from an online brokerage service that allows its clients to trade contracts for difference (CFD) on a variety of underlying instruments, including equities, foreign exchange (fx), commodities, indices, and cryptocurrencies.[4] With low entry barriers and the option to hold long and short positions, the online brokerage data is well suited to investigate the increasing popularity of cryptocurrencies among individual investors.

Our descriptive statistics reveal that cryptocurrency trading became increasingly popular for female and male traders and across different age groups and traders with different trading patterns. In particular, we find that by the end of 2017, 90% of active accounts trade contracts on cryptocurrencies and that on its high, 71% of all executed transactions have a cryptocurrency as the underlying asset. The results of our probit-regression analysis show that men and individuals between 35 and 44 years of age are most likely to engage in cryptocurrency trading. Furthermore, we find that female traders behave in a less speculative manner and consequently realize higher returns on cryptocurrency trades than men.

Our study contributes to literature on cryptocurrencies, active trading, and individual investor characteristics. Our findings may help to improve our understanding of the usage and price movements of cryptocurrencies.

2. The rise of cryptocurrency trading

Our empirical analysis is based on individual-investor data obtained from an online brokerage service operating under a UK-brokerage licence, which self-reports to be the market leader of CFD cryptocurrency trading. The broker allows its clients to trade CFDs on a variety of underlying instruments, including cryptocurrencies. The practice of CFD trading is growing rapidly across the world. For example, the value of CFD transactions

[4]Brown et al. (2010) provide a detailed analysis on the structure and pricing of CFDs. The cryptocurrencies traded through the online broker are are Bitcoin, Bitcoin Cash, Dash, Ethereum, Ethereum Classic, Litecoin, Neo, Ripple, and Stellar.

amounted to 35% of the value of London Stock Exchange equity transactions in 2007 according to the Financial Services Authority. For cryptocurrencies in particular, trading CFD provides investors the potential to engage in cryptocurrency trading through reputable brokers instead of having to do so through less reputable websites that may not be under government oversight. Thus, offering CFD based trading results in lower barriers to entry to engage in cryptocurrency trading. Additionally, it allows investors to engage in short positions, which is not possible if they trade the underlying security. The broker charges transaction fees on the bid/ask spread, with the spreads being within the range assumed by Barber et al. (2014).

The data on 465.926 unique investor accounts spans the period from 1st of January 2014 to 31st of December 2017 and contains investors' demographics characteristics, i.e., gender and age as well as continuous information on trading patterns and performance. Specifically, on a trade basis, opening and closing times, prices, the underlying security, direction, i.e., long or short, and percentage of leverage on the position are recorded. We aggregate the data on a weekly basis.

	Accounts	No. trades	Cryptocurrency	Equity	FX	Commodity	Index	Leverage	Short sales	Holding
					Female					
All	50,424	5.75	22.37%	20.23%	42.01%	10.74%	4.65%	87.20%	35.34%	884
18-24	5,066	5.03	20.98%	23.61%	39.68%	10.58%	5.15%	88.26%	33.39%	769
25-34	19,893	5.71	20.46%	22.98%	41.39%	11.01%	4.16%	86.53%	34.28%	981
35-44	12,989	6.03	22.80%	19.31%	42.14%	11.17%	4.58%	85.26%	36.06%	909
45-54	7,402	6.30	26.68%	15.90%	41.33%	10.67%	5.42%	84.60%	36.44%	759
55-64	3,738	5.31	25.88%	14.33%	45.03%	9.45%	5.31%	91.23%	36.90%	695
>65	1,336	4.55	18.15%	15.85%	54.22%	7.34%	4.43%	114.96%	41.10%	845
					Male					
All	415,301	6.41	32.99%	22.86%	28.25%	11.26%	4.65%	52.19%	29.71%	803
18-24	61,096	5.98	30.22%	27.20%	24.55%	11.91%	6.12%	48.41%	27.69%	741
25-34	180,120	6.32	30.67%	25.24%	28.60%	11.38%	4.11%	53.27%	29.73%	872
35-44	103,697	6.75	34.39%	20.48%	29.27%	11.31%	4.54%	53.28%	30.73%	780
45-54	45,509	6.75	39.84%	16.16%	28.33%	10.78%	4.90%	50.64%	30.03%	677
55-64	17,708	6.45	41.05%	14.00%	30.10%	9.81%	5.03%	52.71%	30.39%	637
>65	7,171	5.15	31.03%	24.87%	31.30%	8.36%	4.44%	50.17%	28.12%	1133

Table 1: Summary statistics on individual brokerage accounts

This table shows the distribution of accounts, number of weekly trades, their distribution across asset classes, and trading patterns across demographic characteristics of our sample of brokerage accounts between 2014 and 2017. We aggregate all characteristics at the investor-level. No. trades is the average number of weekly executed trades. Holding denotes the average hours of an open trading position. Leverage and short sale are provided in percentage.

Table 1 provides summary statistics at the investor-level across demographic characteristics. Our data set consists of 89% (415,490) male traders. 43% (200,100) of account owners are between 25 and 34 years of age. This confirms the under-representation of females and seniors among online retail investors, which has been reported by previous studies that rely on brokerage data from the U.S. (see, e.g., Barber & Odean, 2002; Heimer, 2016).[5] A typical investor in our sample executes 6.3 trades per week. The majority of trades are executed on cryptocurrencies (31.8%), fx (29.74%), and equities (22.57%) across female and male investors and all age groups. Across all asset classes, positions are held, on average, for 811 hours and are 55% leveraged. About 30% of all positions are short.

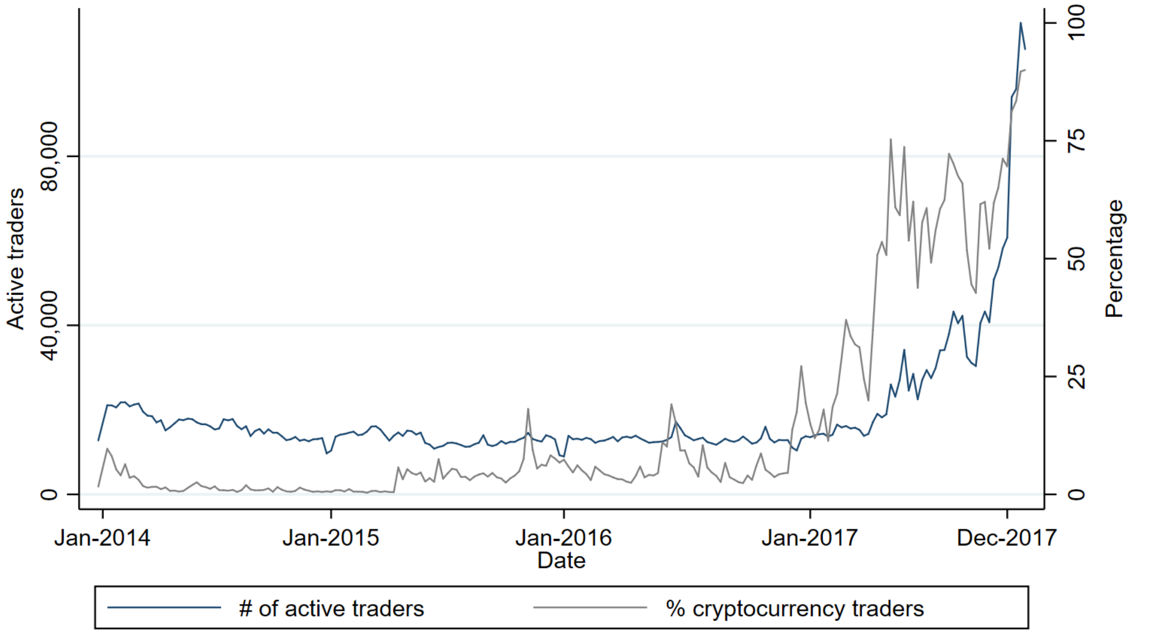

Figure 1: Active accounts and cryptocurrency traders

The figure presents the evolution and absolute number of active investors and percentage cryptocurrency traders over time.

Figure 1 documents the increasing popularity of cryptocurrencies with respect to the number of traders over our sample period. Between 2014 and 2016 the number of active weekly traders, i.e., traders that execute at least one trade in a particular week ranges between about 9,000 and 22,000. In this period, the proportion of traders who execute a cryptocurrency trade is relatively low and does not exceed 20%. However, in 2017 the

[5]For instance, Barber & Odean (2002) report 85% of online brokerage account owners are male and, on average, 49 years old. Heimer (2016) reports an average age of 36 for online retail investors.

absolute number of active traders per week increases from 20,000 to, on average, over 33,000 active traders and reached its all-time high in December 2017 with more than 100,000 active traders in one particular week. The proportion of individuals who traded cryptocurrencies fluctuates between 50% - 75% over the year and peaked at about 90% in December 2017. Specifically, in December 2017, about 90% of all active investors trade cryptocurrencies. The dramatic increase in the proportion of cryptocurrency traders can be attributed to an extensive advertising campaign by the broker during the second half of 2017.

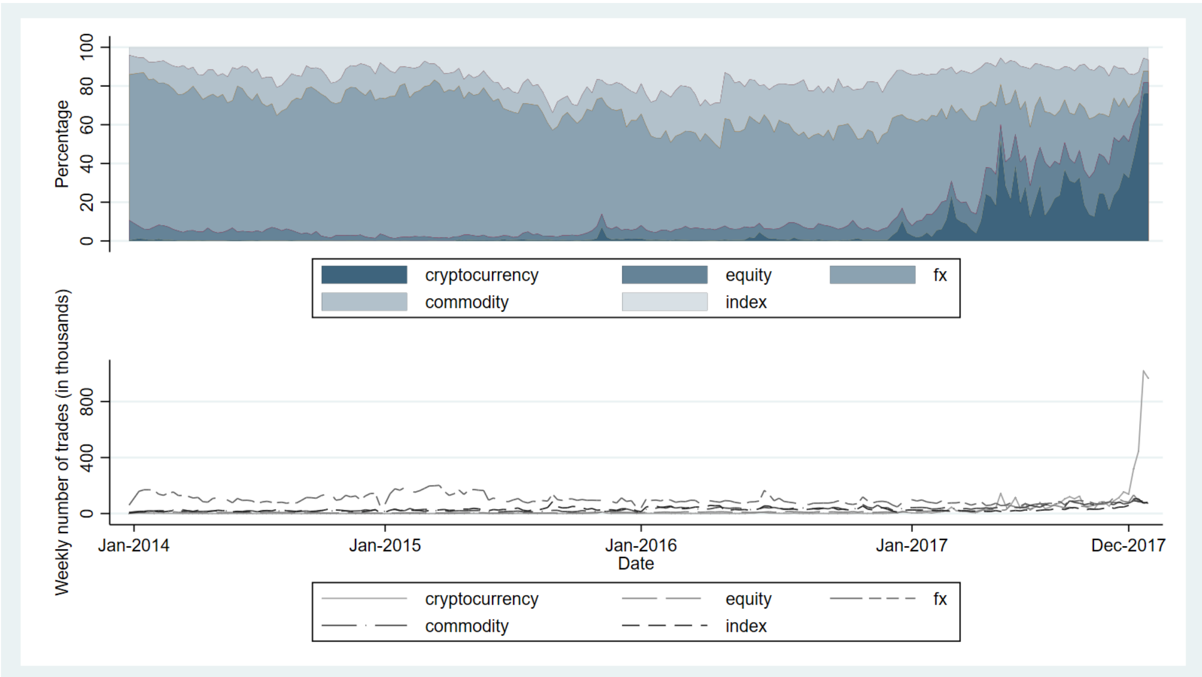

Figure 2: Executed trades across assets classes

The figure presents the distribution (top panel) and absolute number of executes trades (bottom panel) across the different asset classes over time on a weekly basis.

Figure 2 presents the distribution of executed trades (top panel) and absolute number of executed trades (bottom panel) across different asset classes. Between 2014 and 2016 the absolute number and relative proportion of trades on cryptocurrencies is low. In 2017, however, the average number of cryptocurrency trades per week is 88,843 and accounts for, on average, 22% of all trades executed through the online broker. In December 2017, the proportion of executed weekly trades on cryptocurrencies reaches its all-time high of 71%, which coincides with the up to now all-time high of *Bitcoin*, i.e., the currently most popular cryptocurrency. In total, the online brokerage service recorded 5,818,708 transactions on cryptocurrencies in 2017. Figures 1 & 2 indicate that trading cryptocurrencies has become increasingly popular over time and has accounted for a significant portion of individuals' trading activity through the brokerage service, particularly at the end of 2017. When considering the various types of cryptocurrencies, we find that *Bitcoin* is the most popular, representing 35% of all cryptocurrency trades, followed by *Ripple* (23%) and *Ethereum* (21%).

2.1. Who trades cryptocurrencies?

We collapse the data at the investor level to explore the characteristics of cryptocurrency traders. On an individual basis, we calculate the average weekly trading activity and separate traders with respect to their demographic characteristic and trading patterns for each year of our sample period.

Table 2 reports the percentage of traders, who have engaged in at least one cryptocurrency trade separated by gender, age groups, and trading patterns. We separate traders based on their trading characteristics prior to them taking up cryptocurrency trading. Specifically, we average the trading characteristics on a weekly basis and over all weeks an investor has executed at least one trade before s/he engaged in her/his first cryptocurrency trade. The trading characteristics are averaged over the different asset classes. We independently split investors at the median and allocate them into two groups (low or high) for each of the trading characteristics, i.e., number of weekly trades, average position holding hours, leverage, and short sale.

Trading cryptocurrencies became increasingly popular across all age groups and male and female investors. While in 2014 only 16.3% of all accounts traded cryptocurrencies, by 2017, 87.87% of all accounts have engaged in at least one cryptocurrency trade. Trading cryptocurrencies is most popular for investors between 35 and 64 years of age across all years. We observe the highest absolute popularity (90.19%) for male investors between 55 and 64 years of age in 2017. The popularity of cryptocurrency trading changed across investors with different trading characteristics. For instance, between 2014 and 2016

	Gender		No. trades		Leverage		Short sale		Holding		
	Male	Female	Low	High	Low	High	Low	High	Low	High	All
						2014					
All	17.19%	10.13%	11.70%	19.58%	14.10%	17.98%	14.59%	17.48%	19.68%	15.53%	16.30%
18-24	11.97%	8.73%	7.80%	16.87%	9.10%	16.03%	10.03%	13.77%	18.90%	10.59%	11.70%
25-34	16.89%	9.42%	11.53%	19.45%	14.06%	17.71%	14.45%	17.25%	20.04%	15.15%	16.00%
35-44	19.17%	11.20%	13.43%	20.82%	16.44%	19.06%	16.77%	18.83%	20.05%	17.60%	18.10%
45-54	19.61%	11.29%	13.67%	20.49%	16.62%	19.01%	16.57%	19.04%	18.41%	18.23%	18.30%
55-64	18.55%	10.65%	13.99%	18.22%	17.34%	16.74%	16.86%	16.93%	16.94%	16.90%	16.90%
>65	16.10%	7.70%	14.22%	15.25%	15.91%	13.98%	14.13%	15.25%	23.77%	12.61%	14.80%
						2015					
All	29.40%	14.80%	20.85%	28.86%	39.47%	25.81%	31.02%	26.60%	17.48%	32.74%	27.50%
18-24	27.10%	13.20%	17.66%	27.35%	30.74%	24.78%	28.46%	24.68%	16.83%	31.63%	25.70%
25-34	29.70%	14.30%	22.47%	28.98%	39.26%	26.14%	31.84%	26.85%	18.38%	32.73%	28.00%
35-44	30.80%	17.10%	22.73%	30.29%	43.46%	27.13%	33.88%	27.91%	17.86%	34.42%	29.10%
45-54	29.30%	15.90%	18.69%	28.78%	41.58%	25.47%	28.41%	26.73%	16.78%	32.23%	27.00%
55-64	26.30%	12.60%	14.15%	25.71%	40.98%	22.03%	24.40%	23.34%	13.68%	29.31%	23.50%
>65	25.80%	8.20%	17.03%	23.77%	40.00%	19.84%	22.71%	21.90%	13.73%	27.01%	22.00%
						2016					
All	46.37%	31.16%	41.49%	45.22%	57.97%	42.91%	52.80%	42.98%	33.87%	50.31%	44.81%
18-24	41.03%	24.32%	31.70%	40.66%	49.69%	38.17%	46.06%	37.78%	30.27%	46.72%	39.56%
25-34	46.26%	28.91%	43.28%	44.86%	58.31%	42.64%	53.18%	42.75%	34.21%	50.14%	44.71%
35-44	49.03%	34.82%	45.80%	47.80%	61.47%	45.60%	57.14%	45.52%	36.21%	52.38%	47.61%
45-54	47.78%	35.97%	39.86%	46.99%	57.36%	44.67%	53.17%	44.70%	34.54%	50.95%	46.16%
55-64	45.16%	31.72%	37.66%	43.60%	59.54%	40.53%	48.68%	41.50%	31.50%	48.06%	42.80%
>65	42.12%	25.25%	36.49%	40.20%	54.55%	37.58%	43.07%	38.93%	29.89%	44.39%	39.57%
						2017					
All	88.30%	82.85%	97.24%	72.25%	96.99%	70.98%	95.35%	75.63%	93.23%	76.48%	87.87%
18-24	84.14%	75.78%	95.93%	68.17%	95.95%	66.70%	92.46%	71.38%	88.60%	72.72%	83.66%
25-34	88.34%	82.26%	97.31%	72.97%	96.82%	71.49%	95.27%	76.05%	93.08%	77.39%	87.90%
35-44	89.58%	84.30%	97.54%	74.34%	97.25%	73.39%	96.18%	77.34%	94.66%	77.96%	89.15%
45-54	90.05%	85.15%	97.70%	72.51%	97.68%	71.65%	96.43%	76.82%	95.27%	76.04%	89.53%
55-64	90.19%	85.59%	97.62%	71.10%	97.78%	70.20%	96.75%	75.86%	95.52%	74.73%	89.63%
>65	87.27%	83.57%	96.08%	65.11%	97.11%	64.05%	95.42%	71.77%	93.66%	69.06%	86.90%

Table 2: Percentage of cryptocurrency traders across age groups, gender, and trading patterns for each year

This table reports the percentage of traders that have engaged in at least one cryptocurrency trade separated by different characteristics for each year of our sample period. We report the percentage of traders for different gender and age groups. Furthermore, we independently separate individual traders based on their average number of weekly trades, leverage, number of short sales, and position holding time (in hours) of other asset classes before the first cryptocurrency trade. We allocate investors independently into two groups (low or high), by splitting the sample at the median.

cryptocurrency trading was more popular for traders with a high weekly trading activity. In 2015 and 2016, cryptocurrency trading was most popular for traders who hold their positions relatively long, whereas in 2017, cryptocurrency trading was most popular in groups of traders with low position holding times and a low weekly trading activty of other asset classes.

We conduct probit-regression analysis to investigate the probability of investors to engage in cryptocurrency trading. Table 3 reports the marginal effects of our probit-regressions

	Model (1)		Model (2)		Model (4)		Model (4)	
	2014		2015		2016		2017	
Gender								
Female	-0.024	***	-0.060	***	-0.067	***	-0.099	***
	(-13.32)		(-19.68)		(-13.01)		(-18.46)	
Male (reference)	-		-		-		-	
Age group								
18-24	-0.020	***	0.048	***	0.068	***	0.058	***
	(-4.30)		(6.02)		(5.02)		(4.06)	
25-34	0.003		0.037	***	0.062	***	0.097	***
	(0.61)		(4.98)		(4.76)		(6.95)	
35-44	0.005		0.034	***	0.062	***	0.107	***
	(1.16)		(4.56)		(4.72)		(7.61)	
45-54	-0.000		0.024	***	0.054	***	0.093	***
	(-0.04)		(3.05)		(3.98)		(6.45)	
55-64	-0.003		0.006		0.021		0.083	***
	(-0.57)		(0.72)		(1.42)		(5.34)	
>65 (reference)	-		-		-		-	
Trading characteristics								
Low-level of trading (reference)	-		-		-		-	
High-level of trading	0.060	***	0.142	***	0.159	***	omitted	
	(28.69)		(54.11)		(39.61)			
Low-level of leverage (reference)	-		-		-		-	
High-level of leverage	-0.160	***	-0.082	***	-0.055	***	omitted	
	(-52.63)		(-32.84)		(-14.70)			
Low-level of short sales (reference)	-		-		-		-	
High-level of short sales	-0.032	***	-0.023	***	-0.045	***	-0.141	***
	(-16.38)		(-8.34)		(-10.97)		(-48.69)	
Low-level holding time (reference)	-		-		-		-	
High-level holding time	-0.128	***	0.044	***	0.058	***	-0.159	***
	(-65.90)		(17.74)		(16.03)		(-23.42)	
Observations	145,469		89,452		61,094		101,002	
Pseudo R^2	0.10		0.07		0.03		0.02	

Table 3: Probit-regression on engaging into cryptocurrency trading for the first time

The table shows the marginal effects of the cross-sectional probit-regression analysis for each year of our sample period. The dependent variable is a dummy variable that takes a value of one if a trader trades cryptocurrencies for the first time in this particular year, zero otherwise. t-statistics are in parentheses.

for each year of our sample period. Male traders are more likely to engage in cryptocurrency trading than female investors across all periods. In 2015 and 2016, investors who are younger than 55 years of age were more likely to start to trade cryptocurrencies. Except for 2017, investors, who have executed a high number of weekly trades in other asset classes, are also more likely to engage in cryptocurrency trading. In 2017, almost all investors engaged in cryptocurrency trading at some point (see above). Here, all investors who never engage in cryptocurrency trading belong to the above median number of weekly trades in other asset classes-group (variable omitted in the probit regressions). Similarly, all of these investors also belong to the above median leverage-group. In general, investors who use high levels of leverage and engage in more short sales are less likely to engage in cryptocurrency trading. In 2014 and 2017, traders who have hold other positions for a short time are more likely to engage in cryptocurrency trades.

2.2. How do investors trade cryptocurrencies?

Next, we focus on investors who engage into at least one cryptocurrency trade and explore how they vary with respect to their cryptocurrency (1) weekly trading activity, (2) leverage, (3) short sales, and (4) position holding time.

	No. trades	Leverage	Short sales	Holding
p1	0.03	4%	0%	0
p10	0.23	20%	0%	1
p25	0.88	53%	0%	18
p50	1.50	100%	0%	83
p75	3.00	100%	13%	229
p90	5.43	100%	33%	510
p99	16.80	225%	100%	2859

Table 4: Summary statistics on cryptocurrency trading patterns across traders

This table reports the trading patterns of cryptocurrencies across our sample of 239,692 traders who engage in at least one cryptocurrency trade. For each trader, we calculate the average number of weekly trades in cryptocurrencies, associated leverage, short sales, and position holding period in hours.

Table 4 provides information about how cryptocurrencies are traded across our sample of investors. On average, 25% of all accounts trade cryptocurrencies at least three times a week and 50% of the traders hold their positions, on average, longer than three days. Most investors hold cryptocurrency CFDs on leveraged and long positions. Next, we conduct regression analysis to investigate the relationship between traders' characteristics and cryptocurrency trading patterns.

Table 5 provides the result of our OLS-regression analysis over the entire sample period. Our findings show that males and traders between 35 and 54 years of age trade cryptocurrencies more actively (Model (1)). Men and young traders use more leverage (Model (2)) and short sales (Model (3)), but tend to hold cryptocurrency positions for shorter periods than female and older investors (Model (4)). Interestingly, trading activity and leverage in other asset classes are negatively correlated, while short sales and position holding time of other positions are positively correlated with cryptocurrency trading patterns. Specifically, on the one hand, investors who show a high level of weekly trading

	Model (1)		Model (2)		Model (3)		Model (4)	
	No. trades		Leverage		Short sale		Holding	
Gender								
Female	-0.075	***	-0.007	***	-0.018	***	0.029	*
	(-17.23)		(-4.90)		(-12.44)		(1.87)	
Male (reference)	-		-		-		-	
Age group								
18-24	0.041	***	0.033	***	0.015	***	-0.507	***
	(4.02)		(10.29)		(4.77)		(-14.14)	
25-34	0.076	***	0.023	***	0.02	***	-0.274	***
	(7.75)		(7.48)		(7.03)		(-7.84)	
35-44	0.106	***	0.016	***	0.021	***	-0.243	***
	(10.73)		(5.31)		(6.57)		(-6.89)	
45-54	0.110	***	0.015	***	0.013	***	-0.198	***
	(10.75)		(4.64)		(3.92)		(-5.49)	
55-64	0.081	***	0.012	***	0.005	*	-0.159	***
	(7.35)		(3.70)		(1.53)		(-4.10)	
>65 (reference)	-		-		-		-	
Trading characteristics								
Low-level of trading (reference)	-		-		-		-	
High-level of trading	-0.103	***	-0.077	***	0.007	***	-0.820	***
	(-19.47)		(-39.15)		(4.56)		(-56.21)	
Low-level of leverage (reference)	-		-		-		-	
High-level of leverage	-0.209	***	-0.056	***	0.000		-0.783	***
	(-42.39)		(-31.47)		(0.26)		(-58.06)	
Low-level of short sales (reference)	-		-		-		-	
High-level of short sales	-0.113	***	-0.050	***	0.007	***	-0.364	***
	(-35.58)		(-47.14)		(7.09)		(-37.00)	
Low-level holding time (reference)	-		-		-		-	
High-level holding time	-0.235	***	-0.130	***	-0.042	***	0.559	***
	(-64.74)		(-84.11)		(-37.69)		(52.75)	
Constant	1.155	***	0.655	***	0.091	***	4.817	***
	(119.44)		(219.36)		(29.61)		(139.24)	
Observations	239,412		239,412		239,412		239,412	
F-value	5,001		7,150		236.076		3,687	
Adj. R^2	0.17		0.28		0.01		0.13	

Table 5: Cross-sectional OLS-regression on cryptocurrency trading patterns

This table reports the results of our cross-sectional OLS-regression analysis on different cryptocurrency trading patterns for the entire sample period. The sample comprises 239,692 individual traders who engage in a cryptocurrency trade at least once. The dependent variable is the log number of average weekly cryptocurrency trades (Model (1)), the log leverage (Model (2)), short sales (Model (3)), and the log hours of position holding time (Model (4)) related to trades on cryptocurrencies. Standard errors are robust and t-statistics are reported in parentheses.

activity and leverage in other asset classes trade cryptocurrencies less actively and with less leverage. On the other hand, investors who use short sales and hold their positions the longest also tend to show this characteristic when trading cryptocurrencies.

2.3. What happened in 2017?

The results of our analysis in sections 2.1 & 2.2 indicate an increasing popularity of cryptocurrencies during 2017. In 2016, 44.81% of all account owners have engaged in at least one cryptocurrency trade. In the following year, the popularity of cryptocurrency trading among investors increased dramatically. By the end of 2017, 87.87% of investors traded cryptocurrencies at least once. We provide more detailed analysis of the year 2017 to understand the increasing popularity of cryptocurrency trading in this particular period.

Figure 3 shows the distribution of trades (upper panel) and absolute number of trades (lower panel) across different asset classes. In the last two months of 2017, the proportion of trades on cryptocurrencies accounts for more than half of all the trades executed through the brokerage service. Interestingly, the lower panel indicates that the increase in trades on cryptocurrencies does not seem to be associated with a decrease in executed trades in another asset class. Increasing popularity of cryptocurrency trading does not substitute the trading frequency of other asset classes.

Next, we aggregate the brokerage data on a monthly basis to conduct further regression analysis for the year 2017. We use the probit-regression model of section 2.1. Table 6 reports the results of our monthly analysis. In 2017, female investors are less likely to engage into cryptocurrency trading than male investors, which confirms our previous findings. We observe that, from January to March, investors, who have executed a high number of weekly trades in other asset classes, are also more likely to engage in cryptocurrency trading, which is in line with the years 2014 to 2016. However, starting in April 2017, this relationship turns around. Now, especially investors, who have executed a low number of weekly trades in other asset classes, are more likely to engage in cryptocurrency trading. In contrast, the relationship between the usage of leverage and the probability to engage in cryptocurrency trading is very stable and negative across all month in 2017, consistent with the years 2014 to 2016. Interestingly, across single months, cryptocurrency trading seems to be more popular among investors with high holding times.

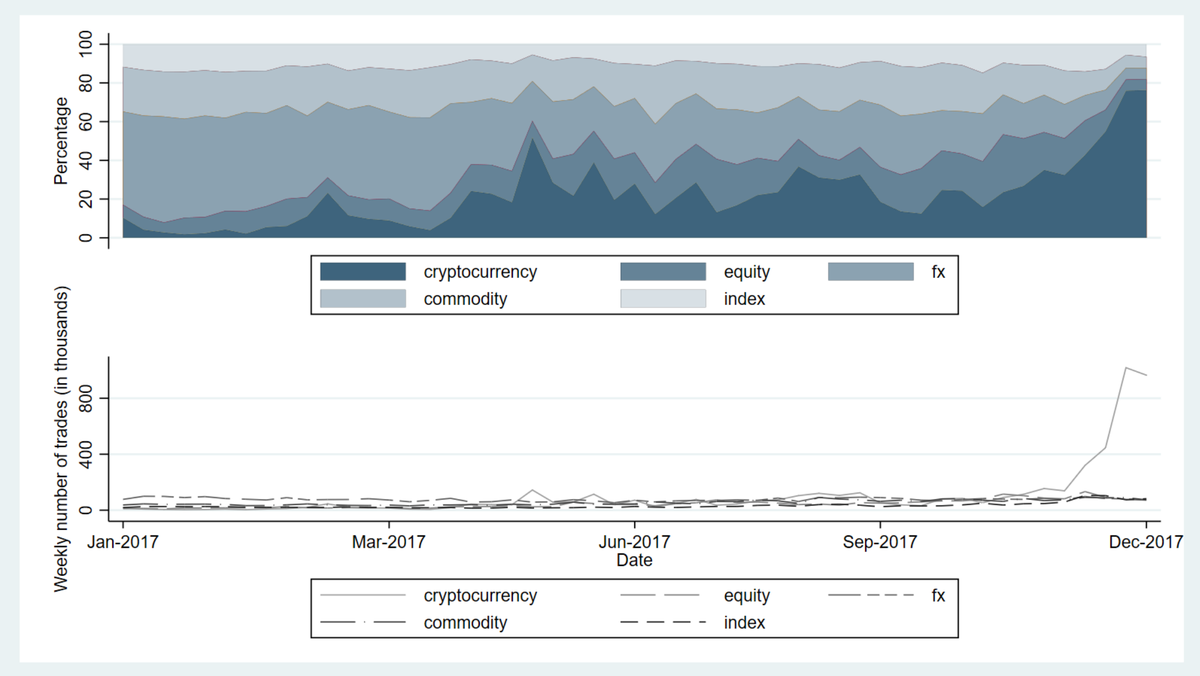

Figure 3: Executed trades across assets classes in 2017

The figure presents the distribution and absolute number of active investors and percentage cryptocurrency traders over time on a weekly basis for 2017.

The proportion and number of investors that execute trades on cryptocurrencies peaks in November and December 2017. Therefore, we conduct more detailed analyses on the trading patterns for these particular months. Specifically, we repeat the OLS-regression analyses of Table 5 on a monthly basis for November and December 2017. Table 7 reports the results of regression analysis for November (Panel A) and December (Panel B) 2017. Confirming our previous findings, female and young investors execute less cryptocurrency trades. In November 2017, we do not observe a significant difference regarding the usage of leverage for positions on cryptocurrencies between between male and female investors and the different age groups. Also, in November 2017, male and female investors do not show a different holding time of positions on cryptocurrencies. In contrast, female investors hold their cyrptocurrency trades for shorter periods in December 2017, and also make less use of leverage. We observe a significant positive correlation between investors age and position holding time in November. In contrast, investors between 25 and 34 years of age tend to hold their positions on cryptocurrencies longer in December 2017.

Panel A: January to June

	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)
	January	February	March	April	May	June
Gender						
Female	-0.083 ***	-0.065 ***	-0.052 ***	-0.103 ***	-0.071 ***	-0.079 ***
	(-13.01)	(-9.60)	(-8.40)	(-14.48)	(-13.43)	(-14.09)
Male (reference)	-	-	-	-	-	-
Age group						
18-24	0.151 ***	0.162 ***	0.274 ***	0.239 ***	0.301 ***	0.246 ***
	(11.05)	(11.47)	(19.44)	(15.72)	(22.85)	(17.30)
25-34	0.160 ***	0.133 ***	0.233 ***	0.184 ***	0.275 ***	0.253 ***
	(12.80)	(10.51)	(17.52)	(13.18)	(21.48)	(18.45)
35-44	0.131 ***	0.0805 ***	0.176 ***	0.124 ***	0.196 ***	0.170 ***
	(10.44)	(6.32)	(13.17)	(8.82)	(15.15)	(12.23)
45-54	0.089 ***	0.032 **	0.106 ***	0.056 ***	0.111 ***	0.096 ***
	(6.84)	(2.46)	(7.67)	(3.88)	(8.32)	(6.71)
55-64	0.060 ***	-0.004	0.056 ***	-0.012	0.055 ***	0.058 ***
	(4.25)	(-0.29)	(3.76)	(-0.79)	(3.80)	(3.84)
>65 (reference)	-	-	-	-	-	-
Trading characteristics						
Low-level of trading (reference)	-	-	-	-	-	-
High-level of trading	0.079 ***	0.049 ***	0.033 ***	-0.048 ***	-0.053 ***	-0.047 ***
	(10.01)	(5.16)	(4.50)	(-5.88)	(-10.87)	(-10.10)
Low-level of leverage (reference)	-	-	-	-	-	-
High-level of leverage	-0.031 ***	-0.018 **	-0.050 ***	-0.022 ***	-0.040 ***	-0.072 ***
	(-4.42)	(-2.19)	(-7.47)	(-2.90)	(-9.05)	(-16.38)
Low-level of short sales (reference)	-	-	-	-	-	-
High-level of short sales	0.058 ***	0.008	0.032 ***	0.045 ***	0.019 ***	-0.008 *
	(8.06)	(0.93)	(4.75)	(5.78)	(4.62)	(-1.87)
Low-level holding time (reference)	-	-	-	-	-	-
High-level holding time	0.046 ***	0.105 ***	0.144 ***	0.132 ***	0.074 ***	0.071 ***
	(8.22)	(15.42)	(27.60)	(21.67)	(21.28)	(20.59)
Observations	77,569	52,078	78,261	54,348	107,261	99,253
Pseudo R^2	0.020	0.023	0.029	0.027	0.029	0.029

Panel B: July to December

	Model (7)	Model (8)	Model (9)	Model (10)	Model (11)	Model (12)
	July	August	September	October	November	December
Gender						
Female	-0.135 ***	-0.080 ***	-0.086 ***	-0.088 ***	-0.049 ***	-0.060 ***
	(-20.38)	(-15.04)	(-13.31)	(-14.32)	(-11.04)	(-9.35)
Male (reference)	-	-	-	-	-	-
Age group						
18-24	0.074 ***	0.155 ***	0.095 ***	0.040 ***	0.087 ***	0.204 ***
	(5.66)	(12.81)	(6.75)	(3.05)	(8.49)	(13.90)
25-34	0.059 ***	0.113 ***	0.086 ***	0.026 **	0.088 ***	0.151 ***
	(4.86)	(9.62)	(6.45)	(2.07)	(8.90)	(10.53)
35-44	0.039 ***	0.071 ***	0.040 ***	0.015	0.068 ***	0.102 ***
	(3.13)	(5.98)	(2.95)	(1.18)	(6.84)	(7.07)
45-54	0.039 ***	0.055 ***	0.044 ***	0.030 **	0.062 ***	0.076 ***
	(3.10)	(4.52)	(3.16)	(2.29)	(6.07)	(5.13)
55-64	0.002	0.033 **	0.001	0.027 *	0.045 ***	0.043 ***
	(0.17)	(2.54)	(0.09)	(1.93)	(4.11)	(2.69)
>65 (reference)	-	-	-	-	-	-
Trading characteristics						
Low-level of trading (reference)	-	-	-	-	-	-
High-level of trading	-0.041 ***	-0.083 ***	-0.127 ***	-0.133 ***	-0.056 ***	-0.059 ***
	(-7.30)	(-18.99)	(-22.99)	(-26.18)	(-19.06)	(-12.25)
Low-level of leverage (reference)	-	-	-	-	-	-
High-level of leverage	-0.070 ***	-0.056 ***	-0.076 ***	-0.054 ***	-0.021 ***	-0.005
	(-13.03)	(-13.29)	(-13.87)	(-10.64)	(-7.09)	(-0.98)
Low-level of short sales (reference)	-	-	-	-	-	-
High-level of short sales	-0.015 ***	0.013 ***	0.025 ***	0.039 ***	0.064 ***	0.081 ***
	(-3.16)	(3.67)	(5.53)	(9.29)	(21.68)	(17.06)
Low-level holding time (reference)	-	-	-	-	-	-
High-level holding time	0.079 ***	0.069 ***	0.072 ***	0.034 ***	0.021 ***	0.055 ***
	(18.78)	(19.84)	(15.76)	(7.45)	(7.23)	(12.21)
Observations	77,369	105,225	76,486	82,251	128,823	74,011
Pseudo R^2	0.012	0.016	0.018	0.017	0.01	0.016

Table 6: Probit-regression on engaging into cryptocurrency trading for the first time on a monthly basis in 2017

The table shows the marginal effects of the cross-sectional probit-regression analysis on a monthly basis in 2017. The dependent variable is a dummy variable that takes a value of one if a trader trades cryptocurrencies for the first time in this particular year and zero otherwise. t-statistics in parentheses.

2.4. How do investors trade cryptocurrencies compared to other asset classes?

We conduct additional sorting analyses to explore how investors trading patterns of cryptocurrencies vary compared to other asset classes, i.e., equities, fx, commodities, and indices. First, we independently rank investors on their average for each of the trading characteristics, i.e., trades, leverage, short sale, and holding with respect to their cryptocurrency investments. Second, we independently allocate investors into five groups (low to high) for each trading characteristic. Table 8 presents the results of our sorting procedure.

We observe differences with respect to investors trading patterns between different asset classes. Specifically, we observe a reverse trading activity with respect to cryptocurrency trading and investments in fx and indices. Investors who trade cryptocurrencies very actively, do not show the same patterns for other asset classes as clearly. We observe similar effects for average position holding periods and usage of leverage. Investors, who hold cryptocurrencies for the longest (1046 hours), on average, hold positions on commodities and indices for the shortest, and vice versa. Except for the 20% of investors, who show the highest usage of leverage, we confirm the reversal effect between investors usage of leverage on cryptocurrencies and fx, commodities, and indices. The table indicates, however, a positive correlation between the usage of short sales of investors across all asset classes. Our results indicate that investors trading patterns, i.e., trading activity, holding periods, and usage of leverage vary across different asset classes. Investors seem to vary their trading strategy with regards to different assets.

Since 2017, the online broker offers its investors to trade cryptocurrencies other than *Bitcoin*, i.e., *Dash*, *Ethereum*, *Litecoin*, *Neo*, *Ripple*, and *Stellar*. Especially in 2017, however, *Bitcoin* has received great public attention compared to other cryptocurrencies and this might, in turn, affect trading patterns of individual investors. Therefore, we explore the differences with respect to trading patterns between *Bitcoin* and other cryptocurrencies. Figure 4 shows the evolution of trading patterns, i.e., number of trades, holding time, usage of leverage, and short sale over time. We calculate the number of weekly trades on *Bitcoin* and other cryptocurrencies in 2017 (upper left panel). Confirming our previous results, cryptocurrency trading peaks at the end of 2017. Surprisingly, other cryptocurrencies are traded with a higher frequency than *Bitcoin*. The trading frequency of *Bitcoin* and other cryptocurrencies is, however, highly correlated (0.79). The average holding period (upper right panel) of *Bitcoin* positions is lower than for other cryptocurrencies and seems to be unrelated (correlation coefficient of 0.25). We observe a significantly positive correlation of usage of leverage (0.57) and short sales (0.66) between *Bitcoin* and other cryptocurrencies.

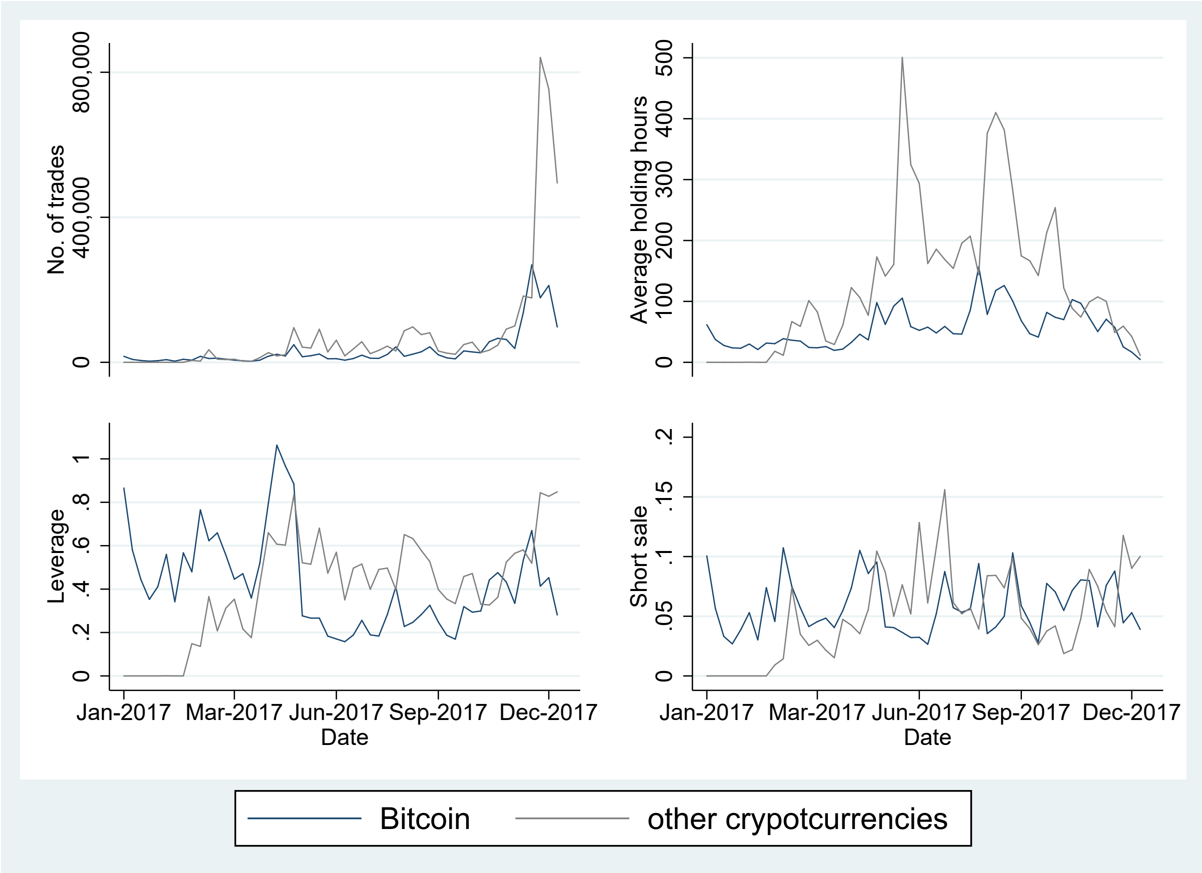

Figure 4: Trading patterns on cryptocurrency level

The figure presents the evolution of average trading patterns on cryptocurrency level. Specifically, we compare the average trading patterns on Bitcoin and all other cryptocurrencies that are traded through the online broker.

2.5. How do cryptocurrency traders perform?

Finally, we explore the performance related to cryptocurrency trading. We differentiate investors based on their demographic characteristics, i.e., gender and age, and their cryptocurrency trading patterns.

Table 9 Panel A shows the average returns across gender and age groups. Overall, female investors realize significantly higher returns than male traders when engaging in cryptocurrency trading. Panel B indicates that performance is not related to the number of weekly executed trades. Specifically, neither the investors with the highest nor least trading activity realize the highest returns. However, the returns on cryptocurrencies seem to positively correlate with the position holding times.

Panel A: November				
	Model (1)	Model (2)	Model (3)	Model (4)
	No. trades	Leverage	Short sale	Holding
Gender				
Female	-0.143***	-0.001	-0.033***	0.008
	(-13.50)	(-0.90)	(-9.81)	(0.40)
Male (reference)	-	-	-	-
Age group				
18-24	-0.062**	0.003	0.000	-0.632***
	(-2.47)	(0.75)	(0.30)	(-15.15)
25-34	0.110***	0.001	0.020**	-0.420***
	(4.51)	(0.17)	(2.79)	(-10.42)
35-44	0.188***	0.002	0.020**	-0.281***
	(7.61)	(0.67)	(2.79)	(-6.93)
45-54	0.174***	0.007*	0.014*	-0.206***
	(6.88)	(1.90)	(1.88)	(-4.94)
55-64	0.085***	-0.005	-0.002	-0.156***
	(3.18)	(-1.14)	(-0.28)	(-3.51)
>65 (reference)	-	-	-	-
Trading characteristics				
Low-level of trading (reference)	-	-	-	-
High-level of trading	0.087***	-0.006***	0.026***	-0.097***
	(13.47)	(-9.30)	(12.45)	(-8.75)
Low-level of leverage (reference)	-	-	-	-
High-level of leverage	0.080***	-0.004***	0.027***	-0.071***
	(12.45)	(-6.14)	(12.95)	(-6.39)
Low-level of short sales (reference)	-	-	-	-
High-level of short sales	0.065***	0.019***	0.029***	0.004
	(9.99)	(21.99)	(14.46)	(0.41)
Low-level holding time (reference)	-	-	-	-
High-level holding time	0.066***	-0.013***	-0.013***	-0.081***
	(10.28)	(-17.96)	(13.16)	(-7.30)
Constant	1.520***	0.648***	0.101***	4.847***
	(61.15)	(172.13)	(13.69)	(117.25)
Observations	98,415	98,415	98,415	98,415
F-value	174.195	155.047	132.745	120.329
Adj. R^2	0.017	0.01	0.01	0.01
Panel B: December				
	Model (1)	Model (2)	Model (3)	Model (4)
	No. trades	Leverage	Short sale	Holding
Gender				
Female	-0.141***	-0.0104***	-0.032***	-0.191***
	(-8.12)	(-2.78)	(-5.23)	(-5.50)
Male (reference)	-	-	-	-
Age group				
18-24	-0.044	0.008	-0.014	0.199**
	(-1.09)	(0.91)	(-0.96)	(2.39)
25-34	0.074*	0.013	0.009	0.230***
	(1.86)	(1.44)	(0.63)	(2.82)
35-44	0.058	0.000	0.013	0.164**
	(1.43)	(0.05)	(0.90)	(1.98)
45-54	0.009	-0.010	0.000	0.109
	(0.22)	(-1.07)	(0.90)	(1.28)
55-64	0.001	-0.013	-0.002	0.028
	(0.02)	(-1.32)	(-0.13)	(0.31)
>65 (reference)	-	-	-	-
Trading characteristics				
Low-level of trading (reference)	-	-	-	-
High-level of trading	0.106***	0.004*	0.023***	0.121***
	(9.89)	(1.91)	(5.34)	(5.22)
Low-level of leverage (reference)	-	-	-	-
High-level of leverage	0.129***	0.011***	0.032***	0.166***
	(12.01)	(5.56)	(7.65)	(7.21)
Low-level of short sales (reference)	-	-	-	-
High-level of short sales	0.169***	0.071***	0.038***	0.189***
	(15.44)	(32.61)	(9.57)	(8.69)
Low-level holding time (reference)	-	-	-	-
High-level holding time	0.097***	0.005**	0.021***	0.141***
	(9.16)	(2.55)	(5.13)	(6.35)
Constant	1.203***	0.491***	0.103***	2.061***
	(29.81)	(54.16)	(7.08)	(24.93)
Observations	48,896	48,896	48,896	48,896
F-value	130.068	119.792	65.937	63.225
Adj. R^2	0.03	0.03	0.01	0.01

Table 7: Cross-sectional OLS-regression on cryptocurrency trading patterns

This table reports the results of our cross-sectional OLS-regression analysis on different cryptocurrency trading patterns. The sample comprises 239,692 individual traders who engage in a cryptocurrency trade at least once. The dependent variable is the log number of average weekly cryptocurrency trades (Model (1)), the log leverage (Model (2)), short sales (Model (3)), and the log hours of position holding time (Model (4)) related to trades on cryptocurrencies. Standard errors are robust and t-statistics are reported in parentheses.

	Crypto	Equity	FX	Commodity	Index	Crypto	Equity	FX	Commodity	Index
	No. trades					Short sale				
All	2.53	0.70	1.62	1.11	0.70	0.10	0.03	0.12	0.09	0.04
Low	0.25	0.84	4.65	2.08	1.48	0.00	0.01	0.09	0.06	0.03
Group-1	0.92	0.51	1.19	0.88	0.52	0.00	0.02	0.10	0.07	0.03
Group-2	1.54	0.58	0.87	0.82	0.50	0.00	0.01	0.09	0.06	0.03
Group-3	2.60	0.56	0.65	0.71	0.40	0.07	0.04	0.20	0.15	0.07
High	7.32	1.02	0.72	1.03	0.63	0.43	0.05	0.11	0.13	0.05
	Holding					Leverage				
All	270.93	141.53	11.54	10.26	3.58	0.82	1.10	22.59	10.19	3.99
Low	2.20	98.23	15.86	10.92	4.95	0.22	1.63	59.40	19.93	8.84
Group-1	28.60	118.86	14.66	12.79	5.25	0.67	2.16	30.33	16.67	6.30
Group-2	84.98	103.02	9.21	9.67	3.14	1.00	0.52	5.24	3.81	1.28
Group-3	192.12	114.27	8.09	9.33	2.59	1.00	0.43	3.96	3.28	1.15
High	1046.74	273.25	9.91	8.57	1.95	1.20	0.74	14.01	7.26	2.37

Table 8: Summary statistics on trading patterns across asset classes

This table reports the trading patterns on cryptocurrencies across our sample of 239,692 traders who engage in at least one cryptocurrency trade. For each trader, we calculate the average number of weekly trades in cryptocurrencies, associated leverage, short sales, and position holding period in hours. We independently rank investors on each of the trading charateristic and allocate them into five groups (low to high).

Mean weekly return on cryptotrades			
	Male	Female	t-test
All	.00090	.00107	7.43
18-24	.00064	.00081	2.85
25-34	.00078	.00091	3.73
35-44	.00094	.00113	4.26
45-54	.00125	.00125	0.02
55-64	.00144	.00143	0.07
>65	.00150	.00142	0.35

Table 9: (Panel A): Return on cryptocurrency trades across demographic characteristics

Mean weekly return on cryptotrades				
	No. trades	Leverage	Short sale	Holding
Low-group	.00007	.00010	.00109	-.00004
Group-2	.00094	.00065	.00111	.00011
Group-3	.00136	.00132	.00110	.00060
Group-4	.00128	.00132	.00079	.00131
High-group	.00097	.00124	.00053	.00263

Table 9: (Panel B): Return on cryptocurrency trades across trading patterns

The table reports the average weekly realized raw-returns at the account-level across traders with different characteristics. First, panel A presents the returns separated across different demographic characteristics, i.e. gender and age groups. Second, for each trader, we calculate the average weekly trades, leverage, short sale, and holding time on cryptocurrencies. We independently rank and allocate traders to five groups (low-level to high-level) for each trading characteristic.

3. Conclusion

This study investigates the increasing popularity of cryptocurrency trading across investors with different demographic characteristics and trading patterns. Trading cryptocurrencies becomes increasingly popular across investors with different gender and age groups. Our findings show that men are (i) more likely to engage in cryptocurrency trading, (ii) trade cryptocurrencies more actively, (iii) hold positions shorter, and (iv) realize lower returns. We also find that the demographics of cryptocurrency traders changed throughout the sample period. The main consistent finding is that men are more likely to engage in cryptoccurrency trading. Finally, we compare the behaviour of investors across multiple asset classes and find that investors vary their trading strategies across asset classes as their trading activity, holding periods, and usage of leverage vary substantially across different asset classes.

We acknowledge the limitation of our data source, which suffers, similar to other studies on online retail investors, from a self-selection bias. The broker in our study is, however, the market leader in CFD trading of cryptocurrencies with 5,818,708 recorded transactions in 2017. As CFD trading enables investors to engage in cryptocurrency trading through established and reputable brokers, we believe that our findings are of interest to understand how existing investors who trade other asset classes behave when trading cryptocurrencies in similar conditions. In conclusion, our findings add to the literature on trading behavior of individual investors and active trading and are important for brokerage services, businesses, and standard setters. Further research might investigate the behaviour of individuals who purchase cryptocurrencies directly as we are unable to analyse direct investments into cryptocurrencies with our data set.

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