An Inside Look into Cryptocurrency Exchanges

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Abstract

Using unique data from a medium-sized cryptocurrency exchange in Asia, we establish 10 facts about cryptocurrency exchanges and cryptocurrency trading. 1) Individuals hold cryptocurrency portfolios of small value, 2) they trade very few cryptocurrencies, 3) their trading patterns are very concentrated, and 4) their trading horizon is very short. 5) Cryptocurrency characteristics explain how much they are traded and how long they are held in investors' portfolios. 6) Most of the trades occur between individual investors and institutional investors and market makers play a minor role in the exchange. 7) It is difficult to benchmark portfolio returns because investors' portfolios are not diversified enough, but 8) institutional investors do not outperform individual investors. 9) Individual investors' make good trading decisions, in the sense that the cryptocurrencies they buy outperform the ones they sell. 10) The same is not true for institutional investors.

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Introduction

Cryptocurrencies have been taking the world by storm since the introduction of Bitcoin in 2009. Recently, the academic community has made significant progress in expanding our understanding of the determinants of cryptocurrency returns: Liu and Tsyvinski (Forthcoming) show that the risk-return profile of cryptocurrencies is largely unrelated to that of other asset classes such as equities, traditional currencies and commodities; Liu, Tsyvinski, and Wu (2019) show that three factors—market, size and momentum—explain the cross-section of cryptocurrency returns; Shams (2020) shows that the highest variation across cryptocurrency returns is explained by a "connectivity" measure that proxies for similarity in investor bases using their trading locations; finally, Makarov and Schoar (2020) show that there are large and recurrent arbitrage opportunities across different cryptocurrency exchanges.

The existing literature is based on exchange-level data where researchers have access to all the transactions and prices across a number of exchanges, but do not have identifiers for the individual or institutional investors that place each trade. As a result, even though the popular news routinely features investors who became multimillionaires trading cryptocurrencies, very little is known regarding how individuals trade cryptocurrencies and how cryptocurrency exchanges operate. For example, who trades cryptocurrencies? Is it mainly individual or institutional investors? What portfolios of cryptocurrencies do these investors hold? What is their investment horizon? And, more importantly, are cryptocurrency traders able to profit from the wild positive and negative cryptocurrency price swings?

In this paper, we provide answers to these questions by gaining unique access to the universe of trading data of a medium-sized cryptocurrency exchange in Hong Kong. Our data allows us to associate every trade on the platform to a unique investor identifier. We also have access to the login activity, the monthly positions as well as the demographic characteristics of all traders on the platform, including whether they are individual retail investors, institutional investors or market makers. Our dataset is extremely detailed as we are also able to identify and remove all the wash-trades on the platform that were either executed by the exchange themselves. We are also able to identify the self-trades initiated by market makers whose main role is to limit arbitrage opportunities across different exchanges. We use this data to provide several novel facts regarding how individuals trade cryptocurrencies and how cryptocurrency exchanges operate.

Fact 1: Individuals hold cryptocurrency portfolios of small value

We start by documenting demographic and portfolio characteristics of cryptocurrency traders. The average retail investor is extremely young—27 years on average—is predominantly male, and has an extremely under-diversified portfolio: he/she holds 2.1 cryptocurrencies on average. The vast majority of retail investors hold one cryptocurrency in their portfolio and only the top 1% of the distribution holds a diversified portfolio of more than 18 assets. Portfolio values are also rather small, the average portfolio value is $330 and even the top 1% of the distribution, retail investor portfolios are worth only $839. Also institutional investors do not have well-diversified portfolios. They hold four cryptocurrencies, on average, for an average value of $71,302 and even the top 1% of the distribution have relatively small portfolios worth $2.5M. Finally, also market makers hold very small positions. The average market-maker holds five cryptocurrencies for an average portfolio value of approximately $7,700, the largest one has only 20 cryptocurrencies for a total value of $52,000.

Trading activity is where we see the biggest differences across investor types. The average retail investor places 464 trades per month on the platform for a total monthly volume of $136,230. These numbers are extremely high, because they are driven by the tail of the distribution that includes high frequency traders placing as many as 12,208 trades per month, for a total monthly volume of $200,605. The median figures are more in line with expectations, with 4 trades and a monthly volume of $27.61. Institutional investors are much more active, with an average of $1.8M trades per month for a total monthly volume of $2.0M. These high averages are also driven by the upper tail of the distribution, but even the median institutional investors is rather active: it places 13,507 trades per month for a monthly volume of $21,190.80. As expected, the trading volume of market makers is higher than that of the other two groups, with a median of 27,676 trades and a total monthly volume of $1.5M.

Facts 2, 3, and 4. Investors trade very few cryptocurrencies, their trading patterns are very concentrated, and their trading horizon is very short

Even though more than 50 cryptocurrencies are traded on the exchange over our sample, the vast majority of investors trade only a handful of cryptocurrencies—the average is 3—and only a handful of investors trade more than 10 different cryptocurrencies. We also observe a very high degree of specialization within institutional investors and market makers, which also trade less than 10 cryptocurrencies. Using cross-sectional regressions, we show that institutional investors and market makers have more concentrated trading patterns than individual investors. We also show that the degree of concentration in investor trades is positively—rather than negatively—related to the number of trades by investors, suggesting that the more individuals trade in cryptocurrencies, the more their trades are concentrated in fewer securities. Trading experience—measured in months—is instead negatively related to the concentration of investor trades, as is investors' wealth and trading horizon.

Fact 5. Cryptocurrency characteristics explain how much they are traded and how long they are held in investors' portfolios

We augment the analysis by documenting what types of cryptocurrencies are traded the most. In doing so, we build a database comprising the characteristics of the various cryptocurrencies, such as their mine-ability, purpose, community supporting them, and release year—among others. We use these cryptocurrency characteristics in two exercises geared to understand the degree to which investors are willing to trade cryptocurrencies and the horizon they are willing to hold cryptocurrencies for. With respect to the first dimension, we find mineable cryptocurrencies are traded more, compared to non-mineable ones. We also find that infrastructure and financial services cryptocurrencies are traded as much as currency cryptocurrencies and that investors trade more often cryptocurrencies maintained by communities and non-profit organizations, compared to private company cryptocurrencies. Along the second dimension, we find that mineable currencies are held for longer periods, that recently released cryptocurrencies are held for shorter ones and that investors hold infrastructure and computation cryptos for shorter periods, compared to currency cryptocurrencies.

Fact 6. Most of the trades occur between individual investors

Our trade data allows us to uncover who is trading with who, because we have the match between the sell and the buy orders on the exchange. Unlike what is commonly reported in equity markets, we show that the majority of trades in our exchange occur between individual investors, with a rather little role played bystanders institutional investors and market makers.

Fact 7. Investor performance is difficult to benchmark

We compute investor returns at the daily and monthly frequency. In both cases, we find that the average investor return is negative. When we benchmark investors' returns using an equally-weighted portfolio of the top 10 cryptocurrencies—which we call the market—we find that the majority of investors have portfolios that are significantly less risky than the overall cryptocurrency market. We also find that there is significant outperformance in the upper- and lower-tail of the investors' distribution, but the average investor does not outperform the market.

Fact 8. Institutional investors do not outperform individual investors

A stylized fact in equity trading that institutional and professional investors outperform individual investors, at least before management fees. The same is not true in cryptocurrencies, where individual investors outperform institutional investors on a risk-adjusted basis. In cross-sectional regressions, we show that investor performance is positively related to attention and portfolio diversification and negatively related to trading activity. Finally, younger investors outperform older ones and females outperform males on a risk-adjusted basis.

Fact 9 and 10. Individual investors' make good trading decisions. The same is not true for institutional investors

One of the common biases highlighted in the equity literature is that the average performance of the assets sold is superior than that of the assets purchased. In our setting, we find instead that the cryptocurrencies purchased outperform the ones sold, when we focus on individual investors. The returns of buys and sells are instead comparable for institutional investors. Furthermore, we find that the performance of the cryptocurrencies purchased by individual investors is superior to that of the cryptocurrencies purchased by institutional investors. These facts are robust to focusing only on the most traded tickers, as well as focusing to up and down markets.

1 Related Literature

There is now a large and growing literature that studies cryptocurrencies and blockchains. Part of this literature studies the viability and design of blockchains, mining pools and smart contracts—see, among others, Cong and He (2019), Cong, He, and Li (2019), and Cong, Li, and Wang (Forthcoming), Saleh (Forthcoming), and Easley, O'Hara, and Basu (2019). A second area focuses on Initial Coin Offerings (ICOs) and the determinants of their success—see Howell, Niessner, and Yermack (2020) and references therein. A third area focuses instead on cryptocurrency returns and the viability of cryptocurrency investments for individuals and institutional investors. A number of papers in this strand of the literature study aggregate cryptocurrency price fluctuations as a function of economic conditions or price manipulation schemes, see Gandal et al. (2018), Griffin and Shams (2020), and Li, Shin, and Wang (2020). Relatedly, Makarov and Schoar (2019) and Makarov and Schoar (2020) study price formation in Bitcoin and the potential for arbitrage opportunities across different cryptocurrency exchanges. Others evaluate whether cryptocurrencies can be considered an individual asset class, along the lines of equities, commodities, and currencies—see Bianchi (2020) and Borri (2019) and Hu, Parlour, and

Rajan (2019). Our paper contributes to this literature by documenting cryptocurrency exchanges operate and how individual investors operate therein. Furthermore, we are the first who can evaluate the performance of individual and institutional investor trades using administrative data directly from the exchange.

A growing body of work studies cryptocurrency returns from an asset pricing perspective. Liu and Tsyvinski (Forthcoming) show that the risk-return profile of cryptocurrencies; Liu, Tsyvinski, and Wu (2019) propose a three factor model to price cryptocurrencies and Shams (2020) shows that the highest variation across cryptocurrency returns is explained by a “connectivity” measure that proxies for similarity in investor bases using their trading locations. Our paper contributes to this literature by exploring the trading preferences at the individual level.

Our paper is also related to the literature that studies the performance of individual and institutional investors. On the retail investor side, the literature has documented the mistakes of individual investors in equity markets. For example, Odean (1999) and Barber and Odean (2000) show that – on average – individual investors trade too frequently and that trading is detrimental to their wealth. Subsequent studies have uncovered substantial cross-sectional variation among investors’ trading performance. Superior trading performance has been linked to investors’ IQ (Grinblatt, Keloharju, and Linnainmaa (2012) and Korniotis and Kumar (2013)), education (Von Gaudecker (2015)), wealth (Calvet, Campbell, and Sodini (2007)), experience (Korniotis and Kumar (2011) and Nicolosi, Peng, and Zhu (2009)), and portfolio concentration (Ivkovic, Sialm, and Weisbenner (2008)). More recently, Frydman, Hartzmark, and Solomon (2017) document that investors make better investment decisions when they sell one asset and quickly buy another one and Gargano and Rossi (2018) study investors’ attention and the relation between attention and investment performance. On the institutional investor side, a very large literature has studied whether mutual fund mangers outperform the market before and after fees and what are the drivers of mutual fund performance, see Kosowski et al. (2006) and Fama and French (2010) among others. Our results provide novel empirical evidence on individual and institutional investors in cryptocurrencies and shows that many stylized facts in equity markets do not hold in cryptocurrencies. For example, in cryptocurrencies we find that individual investors outperform institutional investors and that the common trading biases documented in equity trading for individual investors do not hold in cryptocurrency markets.

2 Data

The data was generously shared by an anonymous Cryptocurrency exchange in Hong Kong in the form of SQL tables, containing information on individual characteristics, positions, trades, and logins.

The investor characteristics table contains information on investor gender, country of residence and birthday. It also identifies institutional investors, individual investors and those users who act as market-makers on the exchange.

The positions table contains all changes in holdings, at the cryptocurrency-investor level, from December 2017 until August 2019. We also have information on the user initial holdings—in December 2017—as well as the holdings at the end of August 2019. We combine these sources to construct beginning of month holdings at the user level.

The trades table contains information of every trade executed on the exchange. This includes all matched buy and sell orders across investors and market makers on the exchange as well as the fees associated with each trade. Finally, the logins table contains information of all investor logins, including the time of the login, the IP address, and the type of device used—desktop/laptop versus mobile devices.

We obtain end-of-day prices for each cryptocurrency from the trades data by keeping the price of the last trade before midnight.

3 Facts About Cryptocurrency Traders

In this section, we report basic facts about cryptocurrency trading. We start by reporting quantities related to investor holdings, trading and attention, computed across all investors, individual investors, institutional investors and market makers. We then analyze which cryptocurrencies are traded the most and whether trading occurs between individual investors directly or through market makers.

3.1 Investor Behavior—Individual Investors

Table 1 reports key characteristics of cryptocurrency individual investors. While more than 1M individuals create an account and login to the platform maintained by the exchange (1,053,975 to be exact), many of them do not complete the KYC survey. As a result, we have demographic information for 173,000 individual investors, which we report in Panel A. Cryptocurrency investors are males on average—64% of them. They also tend to be extremely young—the average age is 28. Interestingly the distribution is skewed to the left, as the median investor is 33 years of age. The youngest 1st percentile of investors is 20 years of age and, at the other extreme, the 99th percentile of investors is 64 years of age. These investors tend to be younger than the ones commonly found in equity trading brokerages. For example, the average investor is 51 years old in Barber and Odean (2001) and Gargano and Rossi (2018) and is 46 years old in D'Acunto, Prabhala, and Rossi (2019). Our Cryptocurrency exchange is also populated by more women than equity platform: 36% of the investors on our platform are women, compared 29% in D'Acunto, Prabhala, and Rossi (2019), 27% in Gargano and Rossi (2018) and 21% in Barber and Odean (2001).

Panel B reports baseline portfolio characteristics for those investors whose accounts are open as of the last day in our sample—August 2019. Cryptocurrency investors are extremely under-diversified. They hold, on average, 2.31 cryptocurrencies; the median number of cryptocurrencies held is only 1 and only very few cryptocurrency investors—the top 1%—hold at least 18 cryptocurrencies in their portfolios. User accounts are relatively small. Once converted to US dollars, the average investor holds approximately $275 in cryptocurrencies. Half of the investors have virtually $0 dollars invested at the of the month. Finally, even at the 99-th percentile, investors hold only $782 worth of cryptocurrency. Once again, these quantities are much smaller than the ones documented in traditional US brokerage data—the median number stocks held in Gargano and Rossi (2018) (Barber and Odean, 2000) is 4 (2.61) for a portfolio value of $15,000 ($16,210)—but more in line with the portfolio holdings in brokerage accounts in developing countries like India—D'Acunto, Prabhala, and Rossi (2019) document the median investor holds 5 assets for a portfolio value of $986.

Panel C focuses on investor attention. Individuals login, on average, twice per month and the vast majority of individuals login only once per month. We observe more logins only in the upper-tail of the distribution. For example, the most attentive 25% of the investor distribution logs in more than twice per month. The top 1% logs in more than 8 times per month—approximately once in four days. Most of the logins occur through the web, and very few through the mobile App. There are two possible (non-mutually exclusive) explanations for this. First, the App introduction was only recent. Second, the information available through the App was limited during the sample we consider and so the investors preferred using the full-fledged website.

Panel D reports results for the trading activity. Only 136,609 out of 1,058,631 users (14%) place at least one trade. Among those who place at least one trade, on average investors trade 1,214 times, with the median investor placing only 4 trades and the top 1% of the investors placing as many as 17,435 trades over the full sample. The total volume per investor is, on average $723,008. This average is mainly driven by the tail of the distribution. The total volume of the median investor is only $27.72 and it is only $67.83 for the top 25% of the distribution. The third quantity we focus on is the average price of the cryptocurrency traded. Cryptocurrency prices tend to be small. The average trade is \$53.95. The median is size is \$0.07 and only the top 1% of the trades exceed \$630.

In the second part of Panel D, we scale the statistics by month. The average investor trades only for a little over one month and only the top 1% of investors trade for more than 12 months. The median investor places four trades per month, with the most active 1% of investors placing as many as 12,055 trades. The effect of this rather fat right tail entails that the average investor trades, on average, 448.18 times per month. The monthly total volume per investor equals \$135,476, the median and $99-th$ percentiles equal, respectively, \$27.61 and \$198,733.

These statistics highlight that investors in cryptocurrencies are significantly different from the ones in equity brokerages. While they trade extremely frequently, the size of their trades is rather small. On the other hand, equity brokerage investors make less frequent, but much larger trades.

3.2 Investor Behavior—Institutional Investors

The results in Table 1 relate to account-holders who self-identify as individual investors, which account for 99.97% of the investors in the sample. A total of 264 investors, however, self-identify as institutional investors. Their portfolio, attention and trading characteristics are reported in Table 2. For institutional investors, we do not have demographic information. Turning to portfolio characteristics, we start finding some significant differences with respect to individual investors. Institutional investors hold 4 cryptocurrencies, on average, for a total value of \$47,877. In the tails of the distribution, we have institutional investors that hold almost \$1.05M in assets (the $99-th$ percentile equals \$1,049,817). As a comparison, note that the median hedge fund in the US has 615 million dollars in AUM, see Crane, Crotty, and Umar (2018). This difference suggests that institutional investors are still rather reluctant to commit large portfolios to cryptocurrencies, at least within the exchange we analyze.

Panel C reports results for logins. The average institutional investors logs in 4.5 times per month on average with some institutional investors logging in every day. Most of the logins are done through the web and very few through the mobile App, as it was for individual investors.

Trading is where we observe the biggest differences with respect to individual investors. Each institutional investor trades, on average, 151,835 times. The median is 189 trades, but already at the $75-th$ percentile we have that investors place 4,877 trades. The average total volume is also very large, $5,296,557 on average, with the top 1% of the most active institutional investors trading $110,600,000 over the sample. Institutional investors also trade more expensive cryptocurrencies: the average price of the cryptocurrencies they trade is $1,251.

The average institutional investor trades on the exchange for a little over 6 months, an horizon five times longer that the equivalent number for individual investors. This translates into 32,614 trades per month, on average, and a total volume of $1,757,443 per month.

These results highlight two facts. First, institutional investors are wealthier and more active, compared to retail crypto investors. Second, institutional investors that trade in cryptocurrencies have very small positions, but trade very often, compared to institutional investors that trade in equities and other major asset classes.

3.3 Investor Behavior—Market Makers

A few of the investors on the platform are designated as market makers. We have a total of 29 institutions that sign up as market-makers, but only 23 of them are active on the exchange. As shown in Panel B, market makers also hold relatively small portfolios. The average number of cryptocurrencies held is only 5, for an average portfolio value of $10,838. Even the market-maker with largest end-of-day positions at the end of August 2019 had a portfolio of 20 cryptocurrencies, for a total value of $74,191.

Market makers also have much higher log-in statistics, compared to individual and institutional investors, possibly because they are constantly logged in to the platform, see Panel C for details.

Once again, the biggest differences with respect to individual and institutional investors' trading are in Panel D. The average market-maker places 450,445 trades over the sample, with the most active market-maker placing as many and 3,263,520 trades. When measured in US dollars, the average total volume per market-maker is $190M, with the most active market maker trading $1.93B. Finally, the average market-maker is present on the platform for a little over 6 months. This translates into 114,314 trades per month, on average, for a total monthly volume per market-maker of $38.4M.

3.4 Who Trades with Who?

Equity exchanges are commonly organized around market makers that operate as counterparties in most of the trades. Cryptocurrency exchanges are different in this respect as the majority of the trades occur by directly matching the purchases and sales orders of retail investors.

We display this fact in Figure 1. The figure reports the percentage of trades with individuals (top row), institutions (middle row) and Market Makers (last row) by individuals (first column), institutions (second column) and market makers (third column). As shown in the Subfigure (a), the vast majority of individuals trade with individuals. The same is true for institutions and market makers: they also predominantly trade with individuals. The second and third row of figures tell a similar story: very few individuals trade with institutional investors and/or market makers and the same is true for institutional investors. The only exception seems to be market makers that tend to trade a lot with other market makers as counter-parties.

4 Facts About Cryptocurrencies Traded

In this section, we provide facts regarding cryptocurrency trading. We start by reporting in Table 4 information regarding the most traded cryptocurrencies. The table is structured as follows. In the first column we report the cryptocurrency rank, by number of trades on the exchange, ranging from one to 20. The second and third column report instead the ticker and the name of the cryptocurrency. The remaining columns describe the main characteristics of each digital asset: column four categorizes digital assets according to their purpose, that is, whether they are designed for *Currency*, *Infrastructure*, *Computation*, *Entertainment*, and *Financial Services*. The fifth column reports the year each cryptocurrency was released. The sixth column reports information regarding who issued and maintains each cryptocurrencies. Here we focus on three categories: *Private firms*, *Non-profit Organizations*, and *Communities*. The seventh column reports whether the currency is minable, that is, whether individuals can acquire units of the cryptoasset by mining its blockchain. Finally, the last column reports the trading volume rank of each cryptocurrency on CoinBase, as of September 30, 2020.

Broadly speaking, the table reveals, first, that the digital assets traded on the exchange are not strictly digital currencies. The purpose of the various digital assets is distributed rather evenly across providing blockchain infrastructure services, financial services, entertainment. Second, while digital assets issued in the early days, such as ETH, LTC and BTC, are mainly maintained by non-profit organizations and communities, more recently digital assets have been issued by private corporations. Third, a large number of cryptoassets traded are non-mineable, which is rather surprising, given that mineable cryptocurrencies are often thought to be more valuable than non-mineable ones by cryptocurrency investors and online forums.[1] Finally, while several large digital assets are ranked very high on both our exchange and CoinBase—see, for example, ETH, LTC and

[1]For more details on the subject, see the following article titled "*Mineable Cryptocurrencies Are Far More Valuable Than Non-Mineable Coins*".

BTC—others are traded heavily on our exchange but have a low rank on CoinBase—see, for example, ZPR, ONG, and ATLS. The fact that the local ranking on our exchange does not align with the CoinBase ranking is an indication that different exchanges are not simply small versions of larger exchanges and are instead likely to represent investors with different preferences and characteristics. Below we describe in more details three digital assets in our sample, together with their characteristics. The first two are rather popular cryptocurrencies (ETH) and (LTC) while the third is less well-known.

The most traded cryptocurrency is Ethereum. Ethereum (ETH) is a smart contract platform that enables developers to build decentralized applications (dapps). ETH is the native currency for the Ethereum platform and also works as the transaction fees to miners on the Ethereum network. Ethereum is the pioneer for blockchain based smart contracts. When running on the blockchain a smart contract becomes like a self-operating computer program that automatically executes when specific conditions are met. On the blockchain, smart contracts allow for code to be run exactly as programmed without any possibility of downtime, censorship, fraud or third-party interference. It can facilitate the exchange of money, content, property, shares, or anything of value. The price of ETH was $168.29 on August 30^{th}, 2019. As shown in the Table, the purpose of ETH is to provide a blockchain infrastructure, it was released in 2015 and it is run by a non-profit organization. The currency is minable and its rank on CoinBase is 2.

The third most traded cryptocurrency on the exchange is Litecoin (LTC). Litecoin is a peer-to-peer cryptocurrency created by Charlie Lee. It was created based on the Bitcoin protocol but differs in terms of the hashing algorithm used. Litecoin uses the memory intensive Scrypt proof of work mining algorithm. Scrypt allows consumer-grade hardware such as GPU to mine those coins. The purpose of the LTC is that of a digital currency, it was issued in 2011 and it is run by a community. The currency is minable and its rank on CoinBase is 8.

The 8^{th} most traded cryptocurrency is the ZPER (ZPR). ZPER is a cryptocurrency and operates on the Ethereum platform that aims to create a decentralized P2P financial ecosystem using smart contract technology. ZPER has a current supply of 1,850,000,000 with 1,255,879,455.759956 in circulation. The last known price of ZPER is 0.0001839 USD. More information can be found at `https://zper.io`.

Table 5 provides a different perspective. It focuses on the cryptocurrency pairs (or "cryptocurrency markets") trade the most, and not on the total number of trades per cryptocurrencies. Panel A shows that buying Ether using Bitcoins—ETH/BTC—is the most common trade across investors in that 8,015 users place one such transaction. Among those who trade ETH/BTC, the average number of trades is 1,159 for a total volume of $478,009. Finally, the average investor is active in this particular trade for 1.51.

Panel B, through D reports results for the cryptocurrency pairs LTC/BTC, XRP/ETH, and BCH/ETH. In two out of three cases, the funding cryptocurrency is Ether and we find that these trades become less and less common across investors. Only 3,165, 1,453, and 1,314 trade the pairs LTC/BTC, XRP/ETH, and BCH/ETH, respectively.

Overall, individuals trade these cryptocurrency pairs for a short period of time—just a little over a month—and, except for the LTC/BTC crypto pair, there is a negative relation between the number of trades per month and the popularity of a currency, indicating that it is the more active and potentially sophisticated cryptocurrency traders that make the less popular cryptocurrency trades.

4.1 How Many Cryptocurrencies Do Individuals Trade?

Figure 2 focuses on the number of cryptocurrencies traded by each investor. The top 2 subfigures focus on individual investors and shows the majority of investors focus on a handful of cryptocurrencies, up to 3. Very few individual investors trade more and only an extremely small percentage of individuals trade more than 10 cryptocurrencies. This suggests that individuals still think about crypto trading as placing individual bets on specific assets rather than forming well-diversified portfolios. Moving on to institutional investors, we find a slightly larger proportion of investors that trade more than just a handful of tickers, but once again, also institutional investors are not creating and trading broad portfolios when it comes to cryptocurrencies. Finally, the results also show a rather high degree of specialization even for market makers, which for the most part trade less than 10 cryptocurrencies.

Overall, the results reported so far highlight a highly fragmented market, where a few actors operate in a handful of securities. We next characterize the degree to which investors concentrate their trades in a few or a larger number of cryptocurrencies as a function of of their characteristics. The results, reported in Table 6, estimate the following baseline regression equation:

$$Herfindahl\_Index_i = \alpha + \beta \boldsymbol{x}_i + \epsilon_i \tag{1}$$

where $Herfindahl\_Index\_i$ is the herfindahl index of the trades placed across securities by each trader in the sample, computed on the basis of the number of trades over the full history of trades placed by each trader.[2] The conditioning information $\boldsymbol{x_i}$ contains four categories of regressors. The first group contains two dummies for the type of trader: *Market Maker* is equal to 1 if the trader is a market-maker and 0 otherwise; *Institutional Investor* is equal to 1 if the trader is an institutional investor and zero otherwise. The second group contains variables related to the experience of the trader: *Total Trades* is the total number trades placed by the traders over the sample period; *Experience* is the total number of months over which the investor placed trades. The third group of variables contains variables related to the intensity with which traders pay attention and act on the platform: *Trades per Month* (*Volume per Month*) is the total number of trades (the total Volume) for each trader in each month. Finally, the last two variables we include are *Average US Price*, the average price paid by the investor for each trade and *Trading Horizon*, the number of months over which a given trader was active. All the regressors have been standardized so that they have a standard deviation

[2] Working with the amount of wealth traded leads to similar results.

equal to 1, meaning that the coefficient estimates are the change in $Herfindahl\_Index\_i$ associated with a standard deviation increase in of each of the regressors.

The results highlight the following facts. First, starting from the first specification that includes only the first group of regressors, market makers and institutional investors display trading patterns that are more concentrated, compared to individual investors, suggesting that they are specializing their trades in a few currencies rather than spreading them evenly across all the ones they trade. When we add the second group of characteristics in the second specification (column 2), the results for the two categorical dummies do not change. The additional regressors instead show that higher trading activity is related to more concentrated trades, rather than less concentrated trades. Experience, on the other hand, is negatively related to the $Herfindahl\_Index\_i$, suggesting that as investors become more experienced their trades become more evenly spread. The additional regressors suggest that, while there is a positive relation between the total monthly trades and the concentration of the trading activity, the relation is negative when measured in terms of dollar volume rather than the number of trades, suggesting that wealthier traders have less concentrated trading patterns. The final two regressors added in the last column are both positive and significant: the larger the trades in (US dollars) and the longer horizon, the more concentrated the trades.

One fact worth highlighting is that the categorical dummies associated with investor characteristics loose large part of their significance when we add the various trading characteristics as regressors, suggesting that a lot of the differences in the concentration of investors' trades is well-explained by their overall trading behavior.

4.2 Which Cryptocurrencies are Traded the Most?

We now turn to the question of which cryptocurrencies are traded the most. While there are in excess of 50 cryptocurrencies with different characteristics traded on the exchange, it is difficult to know *ex-ante* what cryptocurrencies investors would choose to trade more and why. Table 7 reports results of a cross-sectional regression with the following form:

$$Crypto\_N\_Trades_{j,i} = \alpha_i + \beta \boldsymbol{x}_j + \epsilon_{j,i} \tag{2}$$

where $Crypto\_N\_Trades_{j,i}$ denotes the (log) number of trades for a given cryptocurrency pair, say BTC or ETH; α_i represent individuals' fixed effects and $\boldsymbol{x}_j$ are a number of cryptocurrency characteristics that relate to the cryptocurrency traded. The vector $\boldsymbol{x}_j$ contains the following characteristics: *Minable* is a dummy variable that equals one if this currency is minable, zero otherwise. *Release Year* is the release year of each currency. *Currency, Infrastructure, Computation, Entertainment, Financial Services*, and *Others* are dummy variables that equal one if the cryptocurrency is designed for the corresponding purpose, and zero otherwise. The benchmark group is Currency, which contain those cryptocurrencies that are usually regarded as currency, e.g. Bitcoin, Litecoin, and Tether. *Community, NPO*, and *Private* are dummy variables that indicate whether a cryptocurrency is issued and maintained by a community (e.g. Bitcoin), a non-profit organization (e.g. Ethereum), or private company (e.g. Tether). The benchmark group is Private. CoinMarketCap Rank is the trading volume ranks of cryptocurrencies as of Sept 30, 2020. All continuous variables, namely, *Release Year* and *CoinMarketCap Rank*, have been standardized. We include user fixed effects in all specifications. Standard errors are clustered at user level.

Across Specifications (1) through (3) reported in the table, we find that, first, minable cryptocurrencies are traded more, compared to non-minable ones. We also find that newer cryptocurrencies are generally trade less and that higher ranked currencies (across all cryptocurrency markets) are traded more: note that the coefficient on the regressor *CoinMarketCap Rank* is negative exactly because a higher rank in CoinMarket Rank is associated with a lower value of the regressor.

Specification 4 also shows that most investors trade currency cryptocurrencies, as the dummy for the other categories are all negative and, for the most part, significant.

Infrastructure and Financial Services cryptocurrencies, on the other hand, are traded almost as much as currency cryptocurrencies. The cryptocurrencies that are traded the least, among the specific categories, are the ones dedicated to computation infrastructures.

Finally, Specification 5 shows that, compared to private companies cryptocurrencies, individuals trade more often that cryptocurrencies that are maintained by communities or non-profit organizations.

Table 8 reports results of a cross-sectional regression with the following form:

$$Avg\_Horizon\_Trades_{j,i} = \alpha_i + \beta \boldsymbol{x}_j + \epsilon_{j,i} \tag{3}$$

where $Avg\_Horizon\_Trades_{j,i}$ is the average (log) number of days between two trades in the same cryptocurrency but with opposite direction and the vector of covariate $\boldsymbol{x}_j$ is the same as the one in specification 2, and α_i represent investor fixed effects.

Across the five specifications reported in Table 8, we highlight the following findings. First, minable currencies are held longer than non-minable currencies. Second, recently released cryptocurrencies are held for shorter periods by investors. Third, the purpose of the various cryptocurrencies is related to investors' holding horizon. Investors hold infrastructure and computation cryptocurrencies for shorter periods, compared *currency* cryptocurrencies. They hold instead cryptocurrencies designed for entertainment for longer periods. Finally, compared to cryptocurrencies maintained by private companies, cryptocurrencies maintained by communities and non-profit are held for longer periods.

Overall, the results in this section show individuals purchase more often newly released cryptocurrencies that act as a store of value and support decentralized Apps. At the same time, these cryptocurrencies are not held for a long time in investors' portfolios. They are instead quickly sold after the purchase. The results reported so far suggest cryptocurrency markets are still used largely for gambling in that individuals have little interest in holding broad and diversified portfolios of cryptocurrencies for long periods of time.

The short holding periods and the lack of diversification suggest that cryptocurrency investing may not guarantee high risk-adjusted returns to its investors. We assess this hypothesis next, as we construct individual level portfolio returns and assess the performance of each investor.

5 Investor Portfolio Performance

In this section, we construct and analyze investors' portfolio performance. We start with basic portfolio returns, which are computed using end-of-day portfolio holdings and daily returns in US dollars.[3] The distribution of portfolio returns across investors are reported in Table 9: in Panel A we report results at the daily frequency and in Panel B results at the monthly frequency.

In each panel, the first row reports mean, standard deviation and 1^{st}, 25^{th}, 50^{th}, 75^{th} and 99^{th} percentiles of the average returns distribution computed across all individuals with active portfolio positions over the sample. The second reports the distribution of average returns in excess of a benchmark, computed as the equally-weighted return of the 10 most traded cryptocurrencies. At the daily frequency, both the average returns and excess returns are negative. The distribution of daily returns is centered around zero and has relatively thick tails of -11% and +5% at the extremes. The results are rather similar when we focus on returns in excess of the benchmark.

Panel B shows results at the monthly frequency. The monthly frequency results show a slightly different picture. The majority of individuals have negative average monthly returns, while they have positive average excess returns. The difference between the daily and the monthly frequency results is due to a selection bias: a large number of investors, $1-359/471 = 24\%$ of them, do not have positions open for enough days to have their monthly returns computed. They are also the ones with the weakest investment performance. The monthly summary statistics show huge variability in the tails with

[3]Note that this is what the investors should care about, given that the exchange is in Hong Kong and the Hong Kong dollar is pegged US dollar.

monthly average returns of -77% at the 1^{st} percentile and +30% at the 99^{th} percentile. Similar is the variation for excess returns.

To help the reader visualize the cross-sectional variation in monthly returns across individuals, we report in Figure 3 the distribution of the average monthly returns (Subfigure (a)) and the monthly returns in the excess of the benchmark (Subfigure (b)). Two facts are worth highlighting. First, the average investor realizes monthly returns that hover around 0. Second, the realized returns are heavily skewed to the left, with certain individuals experiencing monthly returns lower than 40% and less than 10% of the individuals experiencing returns in excess of 20%.

The excess returns in Subfigure (b) are less negatively skewed and show instead that a fraction of the investors (around 7%) realized average monthly returns in excess of 60%, indicating that the negative skewness in Subfigure (a) was largely driven by periods where the whole cryptocurrency market lost a lot of value, i.e., the COVID-19 crisis.

Next, we perform CAPM regressions, both at the daily and monthly frequency, and report the results in Panels C and D of Table 9. Two facts are worth noting. First, at the daily frequency (Panel C) the Alpha estimates are very close to zero. The 1^{st} and 99^{th} alpha percentiles have t-statistics of -2.28 and 2.76, respectively, which is what we would expect under the null of no outperformance. The results are similar at the monthly frequency (Panel D) where, if anything, we find that the lowest 1 percentile of investors significantly underperform the market, but no investor significantly outperforms the market. Figure 4 reports the histogram of the alpha t-statistic distribution at the daily and monthly frequencies, confirming that there are virtually no investors outperforming and a few investors underperforming the benchmark.

Second, beta coefficients show that the risk of the portfolio held by individual investors is generally lower than that of the top 10 cryptocurrencies. This is mainly because, for many of the investors, some of the portfolio is invested in US dollars that has by construction a return of zero. While there is a small fraction of individuals with beta coefficients greater than 1—the 99^{th} percentile of the beta distribution equals 1.59 at the daily frequency and 1.17 at the monthly frequency—the vast majority of investors have β coefficients well below 1. Figure 5 reports the full distribution of the beta coefficients across the investors that participate in the exchange.

5.1 Explaining the Cross-Section of Investor Returns

In this section, we assess whether we can explain the cross-section of investor returns using their characteristics. We run the following cross-sectional regression

$$Investment\_Performance_i = \alpha + \boldsymbol{\beta} \boldsymbol{x}_i + \epsilon_i \tag{4}$$

where $Investment\_Performance_i$ is the investment performance of investor i measured as either the alpha t-statistic of of investor i computed over the full sample (columns 1 and 3) or the average return in excess of the market (columns 2 and 4); and $\boldsymbol{x}_i$ is vector of investor characteristics contains the following covariates: $total\_logins$: the total number of logins per month; $Institutional\ Investors$, an institutional investor dummy; $Trades\ per\ Month$, the number of trades per month; $Number\ of\ Assets$, the average number of assets; $Portfolio\ Value$, the average portfolio value. Columns 3 and 4 do not include an institutional investor dummy, focus only on individual investors and include demographic characteristics such as age and gender. The results are reported in Table 10.

The negative constant suggests that, on average, individual investors underperform an equally weighed portfolio composed of the top 10 cryptocurrencies. Second, investors' attention—measured by investors' logins—is positively related to investors' performance, consistent with Gargano and Rossi (2018). Third, consistent with Barber and Odean (2000), the more investors trade, the worse they do. Fourth, the more diversified the portfolio, as measured by the total number of assets, the better the investors' performance. Finally, the total value of the portfolio is negatively related to investors' performance, but the effect is economically small. When we compare the results in the first and second column, we find that all the coefficients have the same sign, indicating that whether we measure outperformance in terms of returns in excess of the market or risk-adjusted performance (α), the results are virtually identical.

One of the unique features of our dataset is the ability to observe both institutional investor and individual investors' performance. The coefficient associated with the institutional investor dummy changes across specifications. It is negative and marginally significant when the dependent variable is the alpha t-statistic, and it is positive and significant when the dependent variable is the average return in excess of the benchmark, suggesting that institutional investors outperform individual investors only when risk is not properly taken into account. Once it is, institutional investors significantly underperform individual investors.

In the last two columns, we restrict the sample to individual investors, so we can include demographic characteristics as covariates. The majority of the regressors maintain the same level of significance, with the exception of the number of assets that is now negative and significant, even though economically small. In terms of the demographic variables, age is negative and significant: younger individuals outperform older ones. On the other hand, we find that the male dummy is negative and significant when risk-adjusted returns are used as a measure of performance, it is instead positive and significant when the measure of performance is excess returns, suggesting that males outperform females because they take more risk in their portfolio.

Overall, the results in this section show that it is challenging to explain cryptocurrency traders' performance using standard models like the Capital Asset Pricing Model (CAPM) because investors tend to be rather under-diversified. They also show that few investors outperform an equally weighted portfolio that purchases the most traded commodities in the exchange. In the next section, we move from analyzing individual investors' portfolio performance to analyzing the performance of their individual trades.

6 Investor Trading Performance

A large literature has shown that, in equities, individual investors tend to make systematic investment mistakes, see Barber and Odean (2007), Barber et al. (2009), Gargano and Rossi (2018) and D'Acunto, Prabhala, and Rossi (2019) and references therein for examples. One of the most common is that they purchase assets that underperform the ones they sell. In this section, we analyze whether this very robust finding holds in cryptocurrencies for individual investors, institutional investors and across different phases of the business cycle.

6.1 Individual Investor Trades

We start with the performance of the trades placed by individual investors. Figure 6 reports results from computing the average returns associated with the cryptocurrencies purchased (blue solid lines) and sold (red dotted lines) in the 70 days before they are traded (left subfigures) and in the 70 days after they are traded (right subfigures). Vertical bars represent 95% confidence intervals. The first two sub-panels reports results using raw returns; the second two sub-panels returns in US dollars; and the last two sub-panels report returns in excess of the benchmark in US dollars.

Focusing on the first two sub-panels that study simple returns before and after a given cryptocurrency is traded, the data suggests that, on average, individual investors sell cryptocurrencies that have performed better, compared to the ones they purchase. This is somewhat surprising, given that it is the opposite of what we commonly observe in equity trading. What is even more surprising is the performance *after* cryptocurrencies are purchased or sold. Here we have that the cryptocurrencies purchased outperform the ones sold, which is—once again—the opposite of what the literature has uncovered in equity trading. One may wonder whether the result is due to how returns are computed. Even when we compute the returns in US dollars as well market-adjusted returns in US dollars, we find that the results are very similar both qualitatively and quantitatively. Hence, our baseline results are not the artifact of how returns are computed.

6.2 Institutional Investor Trades

When we repeat the analysis for institutional investors in Figure 7, we obtain very different results. At all horizons and for all returns computations, we find that cryptocurrency purchases and cryptocurrency sales have the same performance. That is, we do not detect a difference in performance between the cryptocurrencies that are sold and the ones that are instead purchased either before or after the trade is placed.

Note that, while the confidence intervals seems larger for institutional investors, they are just the results of the range of the y-axis being smaller in Figure 6 compared to Figure 7. When comparing the performance of institutional and individual investors, we focus on the last sub-panels (sub-panels (f)) of Figures 6 and 7. In line with the results in Table 10, we find that individual investors' trade are, on average, superior to those of institutional investors. The risk-adjusted performance of crypto purchases by individual investors ranges from 0 to -0.3% at horizons ranging from 1 to 70 days. On the other hand, it ranges from -0.5% to -0.7% over the same horizons for institutional investors.

6.3 Heterogeneity Across Tickers Traded

As a third exercise, we compute the trading performance across the most heavily traded cryptocurrency pairs, that is, ETH/BTC, IOVC/BTC, and CCCX/ETH. The results are reported in Figure 8, where we focus on market-adjusted returns expressed in US dollars. The results highlight three facts. First, the results we report across all cryptocurrencies also hold true for the 3 most-traded cryptocurrencies, that is, cryptocurrencies purchased outperform the ones sold, on average. Second, for certain cryptocurrency pairs we find significantly positive average risk-adjusted returns. See, for example, the currency pair IOVC/BTC, where the risk-adjusted returns decline from 1.5% to 0.2% as we move from

1-day to 70-day horizons.

Overall, the results in this section confirm that the average results across all cryptocurrencies hold also for the most traded ones.

6.4 Results in Up and Down Markets

In this section, we condition the trading performance on whether the trades were place in up or down markets. Up market are defined those days where the average return on the top 10 traded cryptocurrencies over the previous 7 days is greater than zero, while down markets are defined those where the average return on the top 10 traded cryptocurrencies over the previous 7 days is smaller than zero. The results are reported in Figure 9. While we did not detect discernible patterns on cryptocurrency performance before the trades are placed, there is a clear indication that individuals make better trades in down markets. That is, in down markets the cryptocurrencies they purchase outperformed the ones they sell. Furthermore, at least at short horizons we find that the purchases have positive and significant performance. The results for institutional investors show instead that there is virtually to superior or inferior performance of purchases or sales in up or down markets.

6.5 Results at the Intra-Day frequency

The results reported so far are computed at the daily frequency, meaning that we aggregate the daily trades and compute the performance of these trades over the following 70 days. An alternative avenue we can pursue, given the richness of our data, is to estimate the our results at the 5 minutes interval and compute the performance of the trades at hourly intervals. This should be able to tell us whether the high frequency trades sometime implemented by cryptocurrency traders are at all profitable. The answer to this question seems to be no, as shown in Figure 10.

There is some slight evidence that purchases outperform sales for individual investors, as shown in the right Subfigure (b). However, the difference is not statistically significant.

The results for institutional investors Subfigure (d) show instead that the performance is virtually identical.

7 Conclusions

Using unique data from a medium-sized cryptocurrency exchange in Hong Kong, we establish 10 facts about cryptocurrency exchanges and cryptocurrency trading. 1) Individuals hold cryptocurrency portfolios of small value, 2) they trade very few cryptocurrencies, 3) their trading patterns are very concentrated, and 4) their trading horizon is very short. 5) Cryptocurrency characteristics explain how much they are traded and how long they are held in investors' portfolios. 6) Most of the trades occur between individual investors and institutional investors and market makers play a minor role in the exchange. 7) It is difficult to benchmark portfolio returns because investors' portfolios are not diversified enough, but 8) institutional investors do not outperform individual investors' performance. 9) Individual investors' make good investment decisions, in the sense that the cryptocurrencies they buy outperform the ones they sell. 10) The same is not true for institutional investors.

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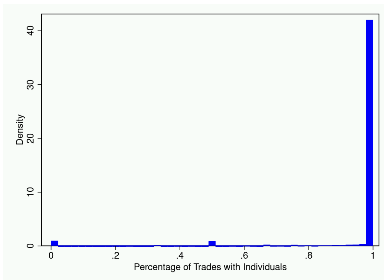
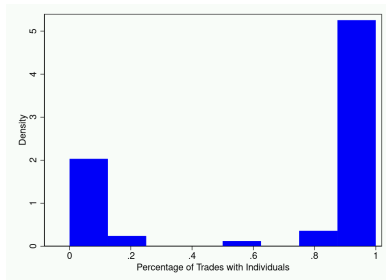
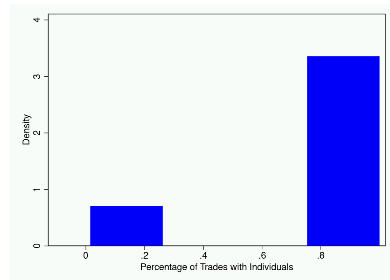
Figure 1. Who Trades with Who?



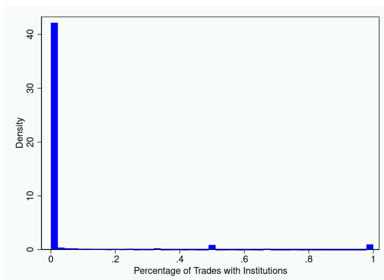
(a) Individuals



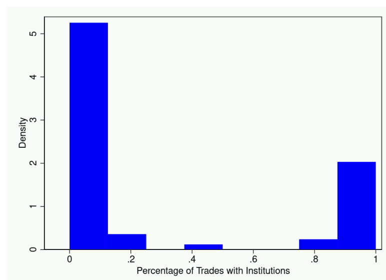
(b) Institutions



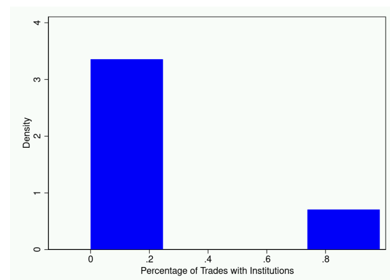
(c) Market Makers



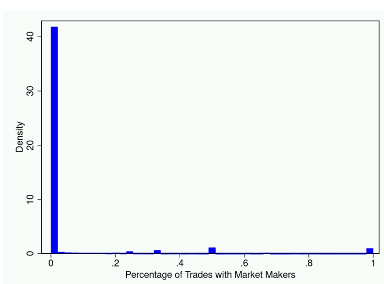
(d) Individuals



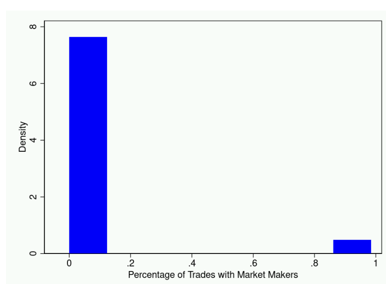
(e) Institutions



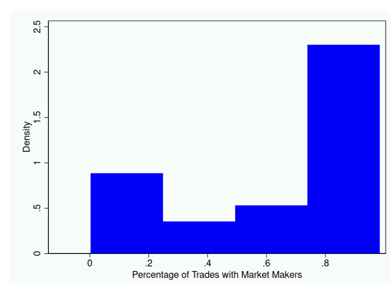
(f) Market Makers



(g) Individuals



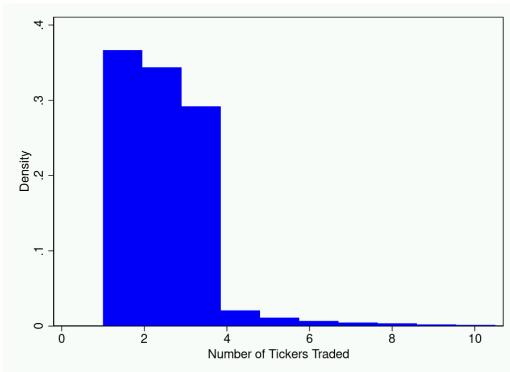
(h) Institutions



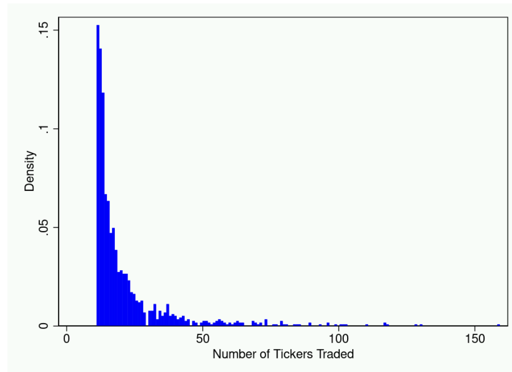
(i) Market Makers

This figure reports the percentage of trades with individuals (top row), institutions (middle row) and Market Makers (last row) by individuals (first column), institutions (second column) and market makers (third column).

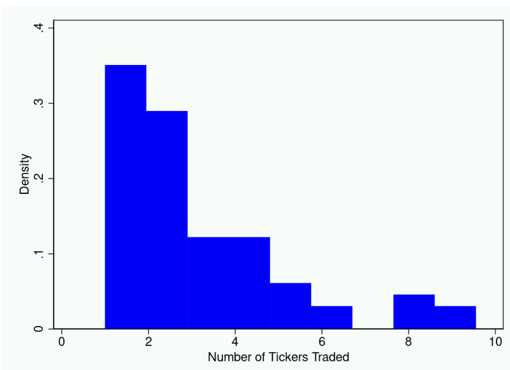
Figure 2. Number of Cryptocurrencies Traded



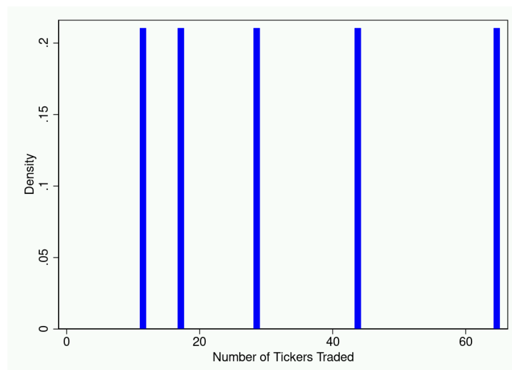
(a) Individual Investors Part 1



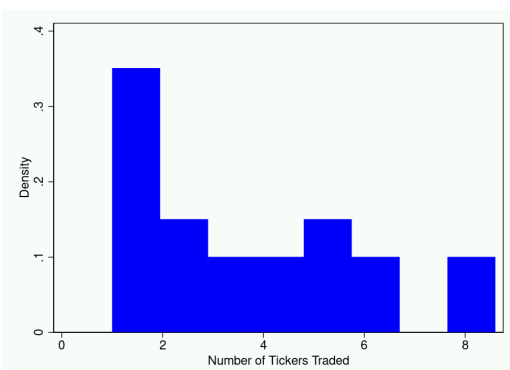
(b) Individual Investors Part 2



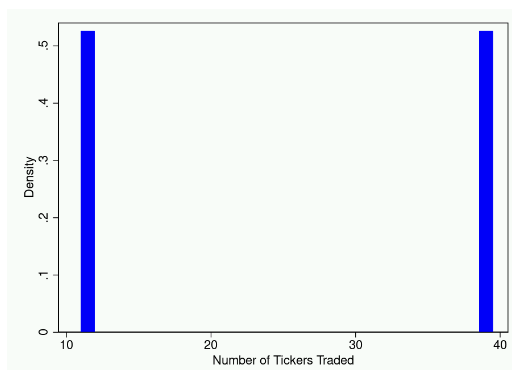
(c) Institutional Investors Part 1



(d) Institutional Investors Part 2



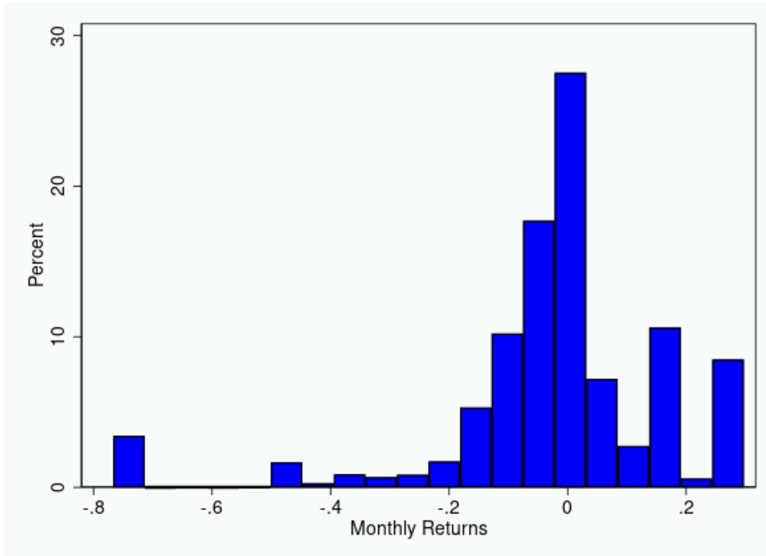
(e) Market Makers Part 1



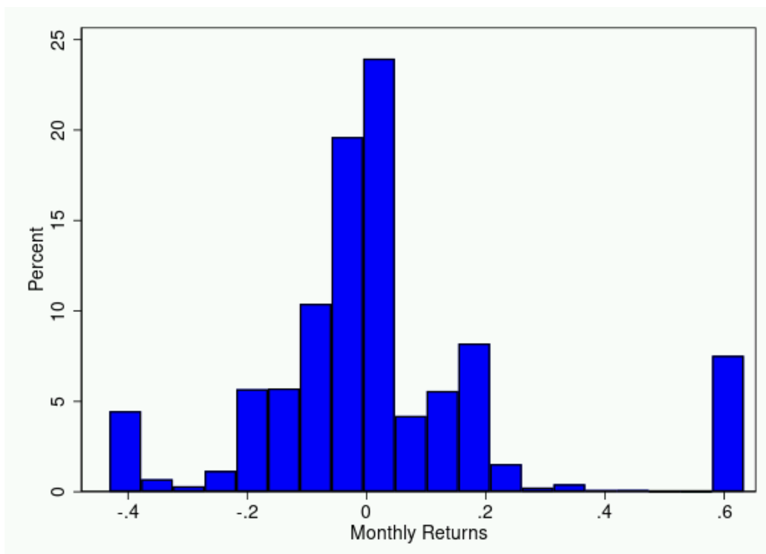
(f) Market Makers Part 2

This figure reports the number of cryptocurrencies traded by investors—categorized in individual investors, institutional investors and market makers. For each investor category, the left panel reports the distribution of trades for those who trade less than 10 currencies, while the right panel reports the distribution of trades for those that trades more than 10 currencies.

Figure 3. Cross-sectional Monthly Returns Distribution



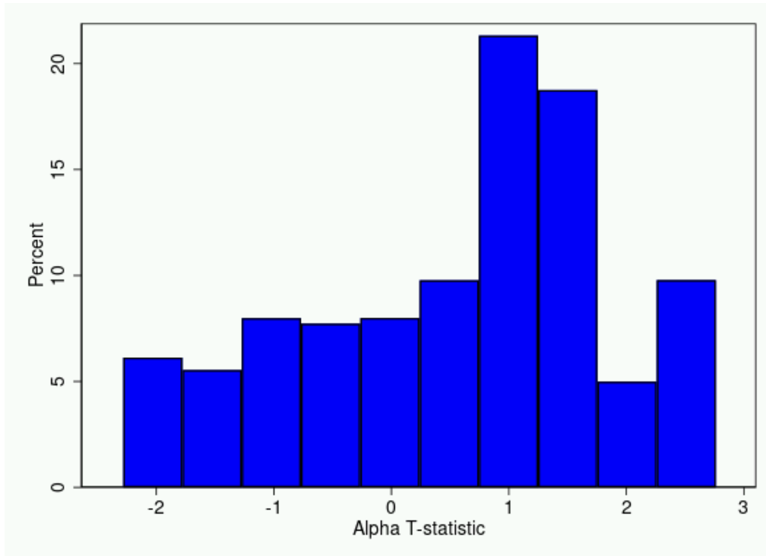
(a) Monthly Returns



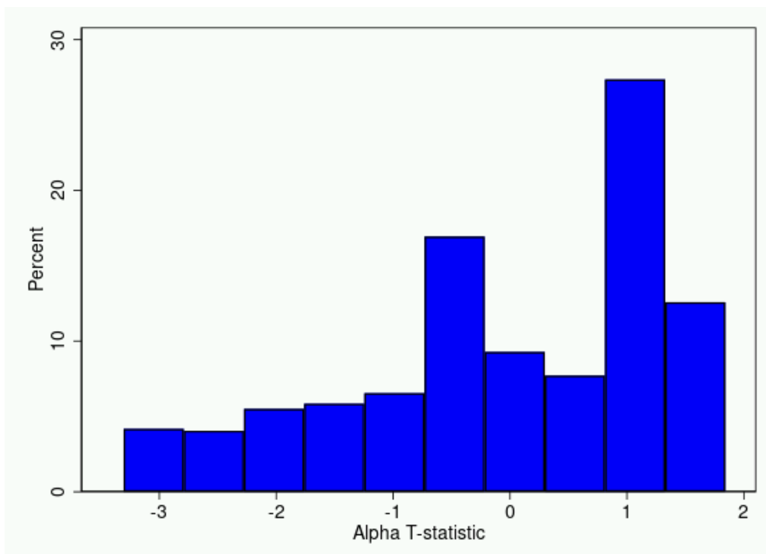
(b) Monthly Returns in Excess of the Benchmark

This figure plots the cross-sectional distribution of the of the average monthly returns, computed across all users in the sample in Panel A. Panel B reports instead the returns in excess of a cryptocurrency benchmark—the average return on the 10 most traded cryptocurrencies.

Figure 4. CAPM Regression Results—Alpha Estimates



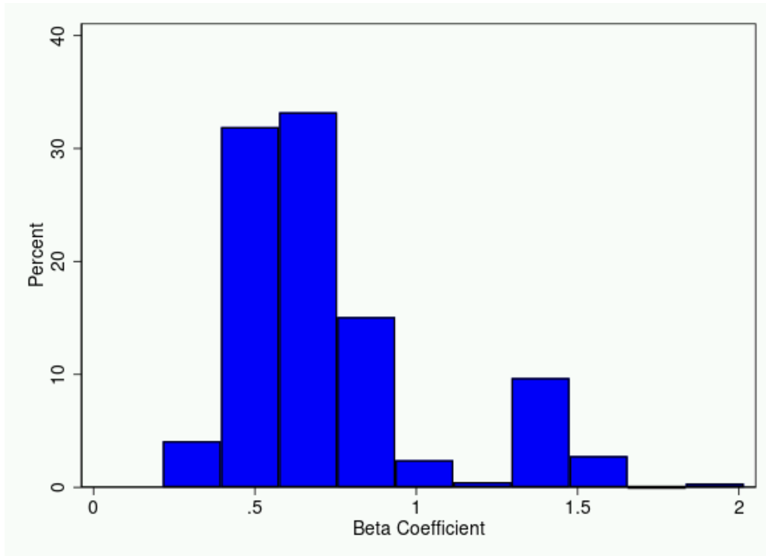
(a) Alpha T-statistic from CAPM Regressions: Daily Frequency



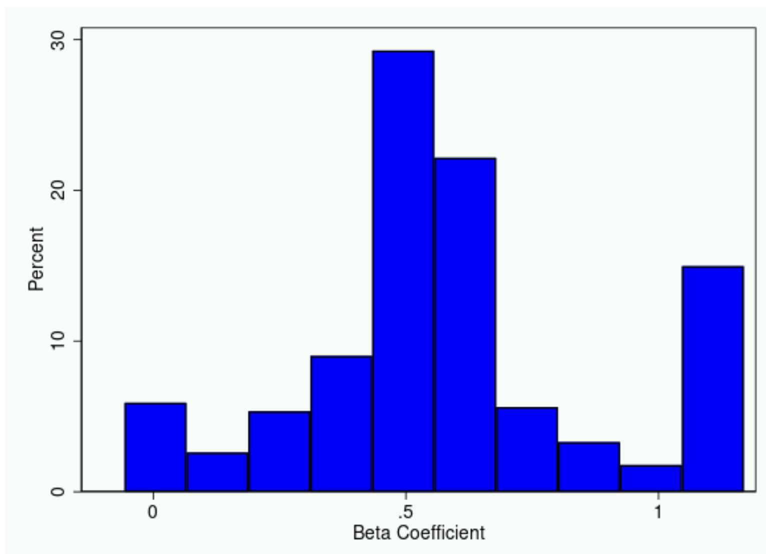
(b) Alpha T-statistic from CAPM Regressions: Monthly Frequency

These figures report the cross-sectional distribution of CAPM alphas, estimated across all cryptocurrency investors. The results in Panel A are computed at the daily frequencies. The ones in Panel B are computed at the monthly frequency.

Figure 5. CAPM Regression Results—Beta Estimates



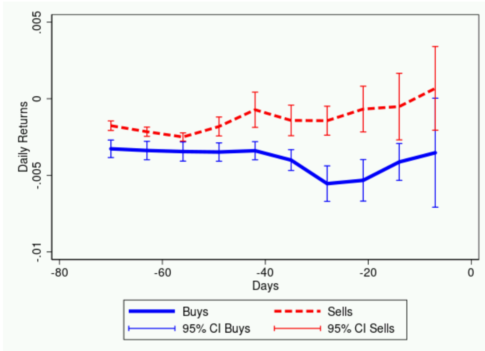
(a) Beta Coefficient from CAPM Regressions: Daily Frequency



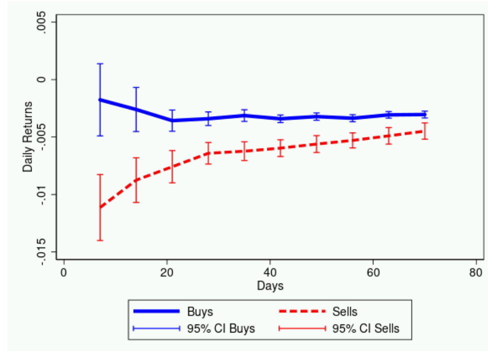
(b) Beta Coefficient from CAPM Regressions: Monthly Frequency

These figures report the cross-sectional distribution of CAPM betas, estimated across all cryptocurrency investors. The results in Panel A are computed at the daily frequencies. The ones in Panel B are computed at the monthly frequency.

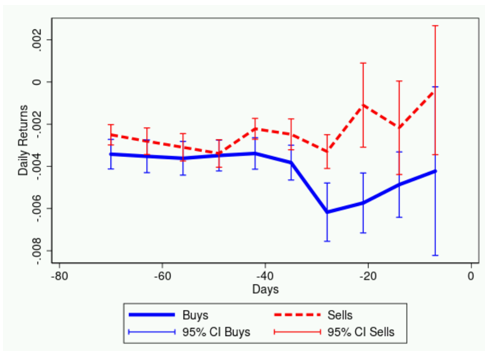
Figure 6. Trading Performance: Individual Investors



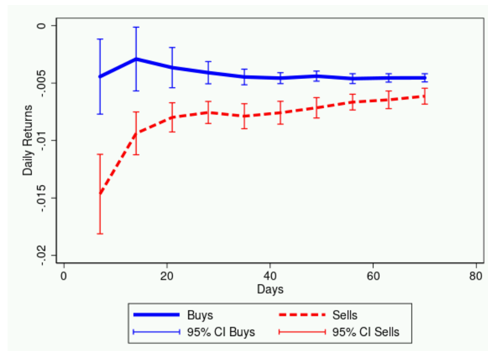
(a) Returns Before



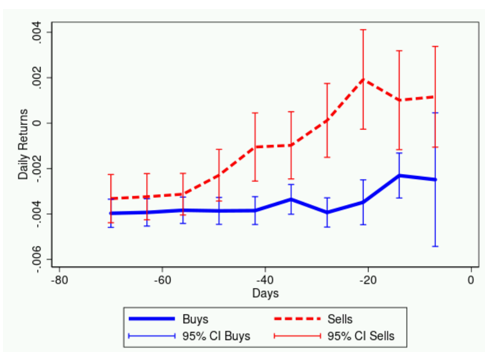
(b) Returns After



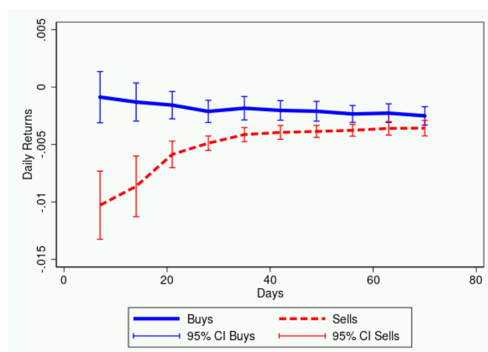
(c) Returns in USD Before



(d) Returns in USD After



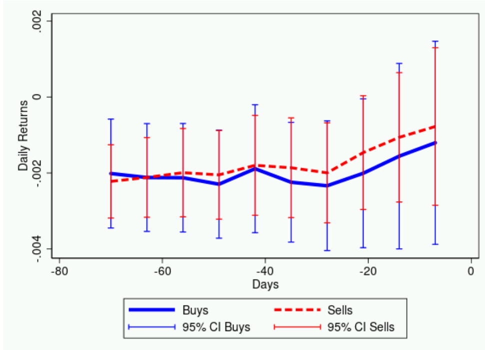
(e) Adjusted Returns in USD Before



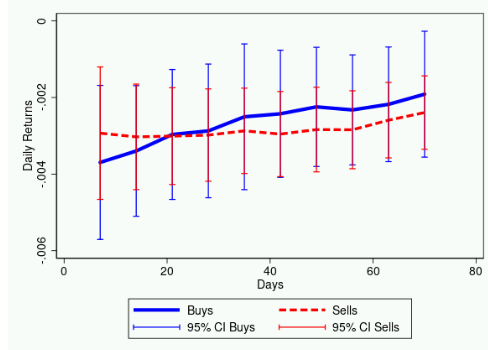
(f) Adjusted Returns in USD After

This plot reports the performance of cryptocurrencies before they are traded (left panels) and after they are traded (right panels) computed across only the trades of individual investors. The results are computed at the daily frequencies and the buys are reported in blue while the sells are reported in red. The vertical bars represent 95% confidence intervals. The first row report results for simple returns, the second for returns computed in US dollars, while the third reports results in US dollars, adjusted for the average return in US dollars of the top 10 traded cryptocurrencies.

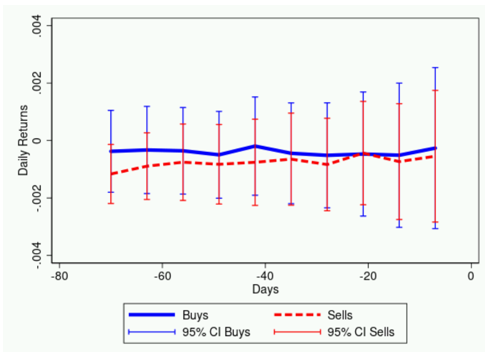
Figure 7. Trading Performance: Institutional Investors



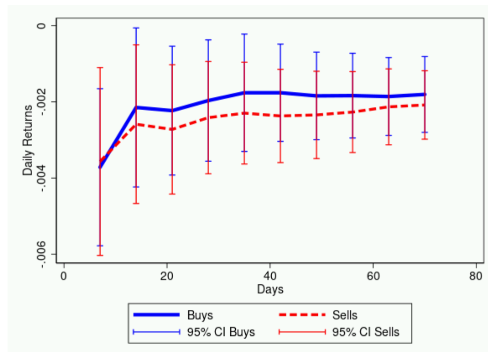
(a) Returns Before



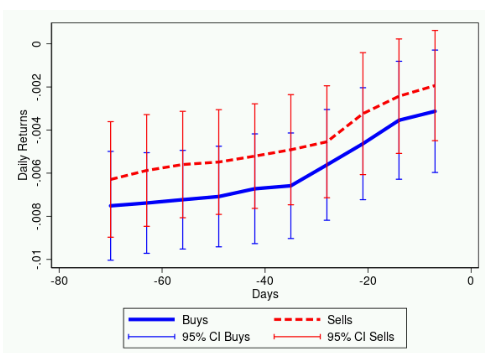
(b) Returns After



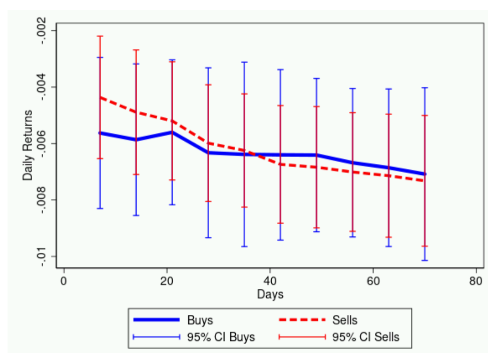
(c) Returns in USD Before



(d) Returns in USD After



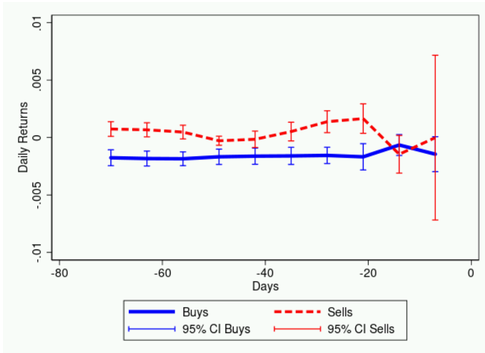
(e) Adjusted Returns in USD Before



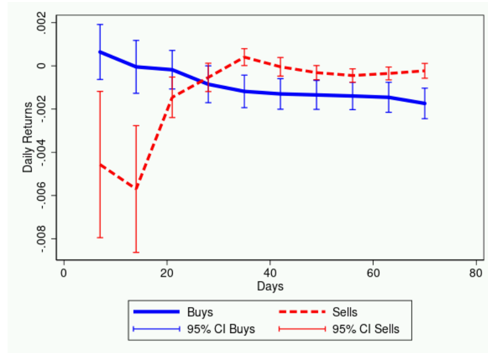
(f) Adjusted Returns in USD After

This plot reports the performance of cryptocurrencies before they are traded (left panels) and after they are traded (right panels) computed across only the trades of institutional investors. The results are computed at the daily frequencies and the buys are reported in blue while the sells are reported in red. The vertical bars represent 95% confidence intervals. The first row report results for simple returns, the second for returns computed in US dollars, while the third reports results in US dollars, adjusted for the average return in US dollars of the top 10 traded cryptocurrencies.

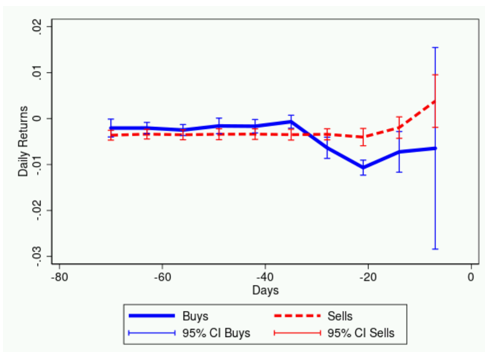
Figure 8. Trading Performance Across Tickers



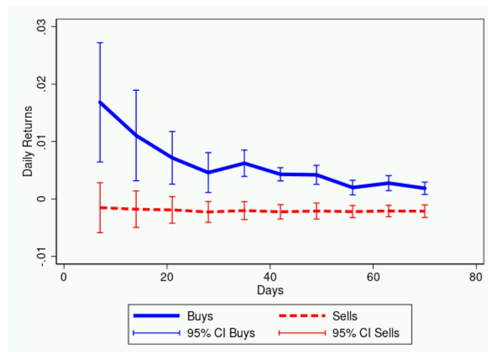
(a) Adj Returns in USD Before: ETH/BTC



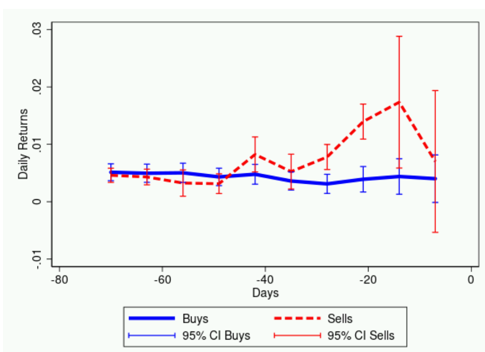
(b) Adj Returns in USD After: ETH/BTC



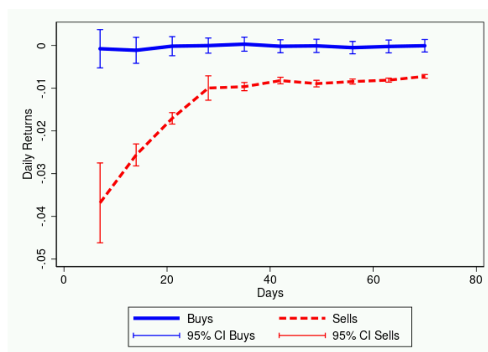
(c) Adj Returns in USD Before: IOVC/BTC



(d) Adj Returns in USD After: IOVC/BTC



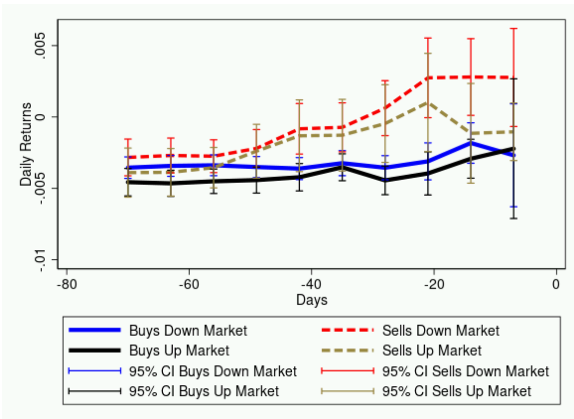
(e) Adj Returns in USD Before: CCCX/ETH



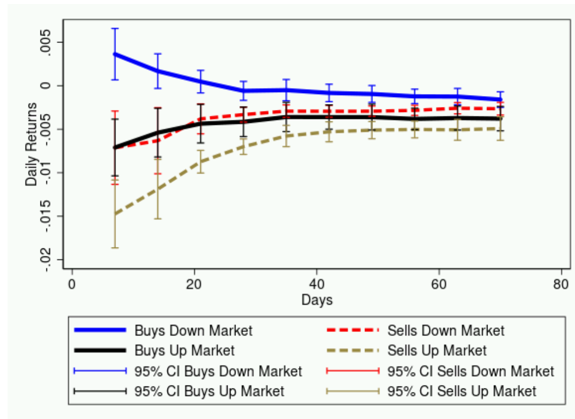
(f) Adj Returns in USD After: CCCX/ETH

This plot reports the performance of cryptocurrencies before they are traded (left panels) and after they are traded (right panels) computed across the six most traded cryptocurrency pairs. The results are computed at the daily frequencies and the buys are reported in blue while the sells are reported in red. The vertical bars represent 95% confidence intervals. Performance is computed as returns in US dollars, adjusted for the average return in US dollars of the top 10 traded cryptocurrencies.

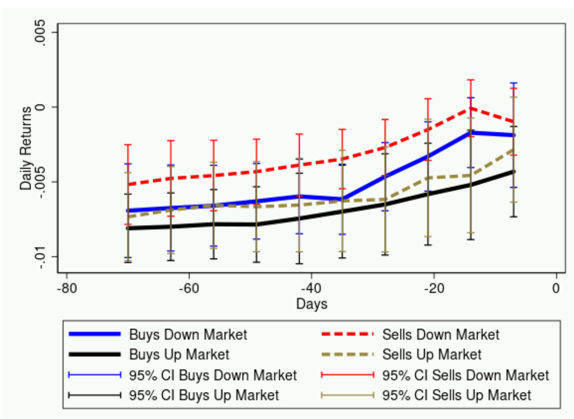
Figure 9. Trading Performance in UP Markets and DOWN Markets



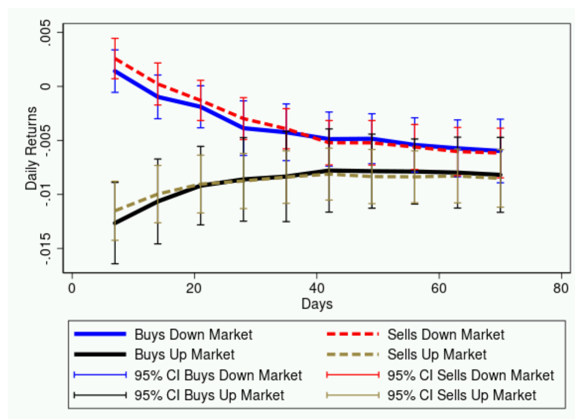
(a) Before: individual investors



(b) After: individual investors



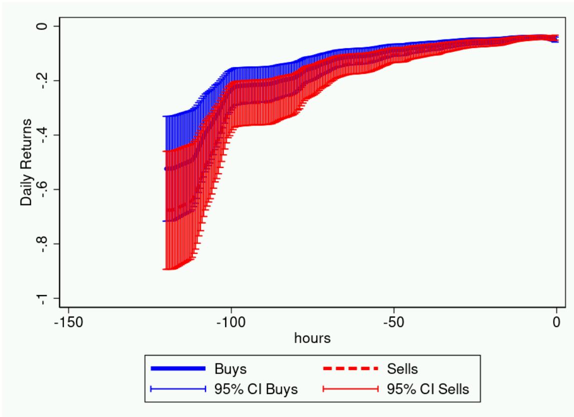
(c) Before: institutional investors



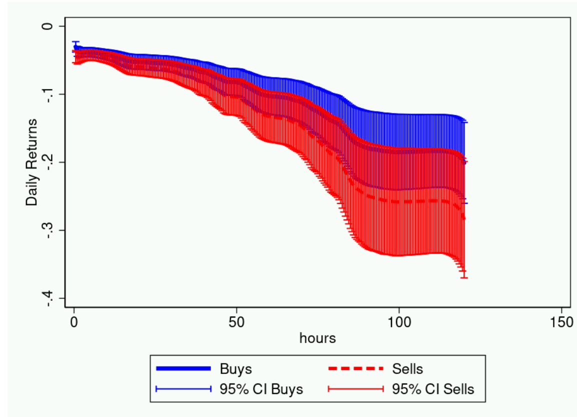
(d) After: institutional investors

This plot reports the performance of cryptocurrencies before they are traded (left panels) and after they are traded (right panels) computed across the trades of individual investors in the top panel and institutional investors in the bottom panel, conditioning on up and down markets. Up market are defined those days where the average return on the top 10 traded cryptocurrencies over the previous 7 days is greater than zero, while down markets are defined those where the average return on the top 10 traded cryptocurrencies over the previous 7 days is smaller than zero. The results are computed at the daily frequency and the buys in down markets are reported in blue while the sells in down markets are reported in red. The buys in up markets are reported in black while the sells in up markets are reported in gold. The vertical bars represent 95% confidence intervals. Returns are reported in US dollars, adjusted for the average return in US dollars of the top 10 traded cryptocurrencies.

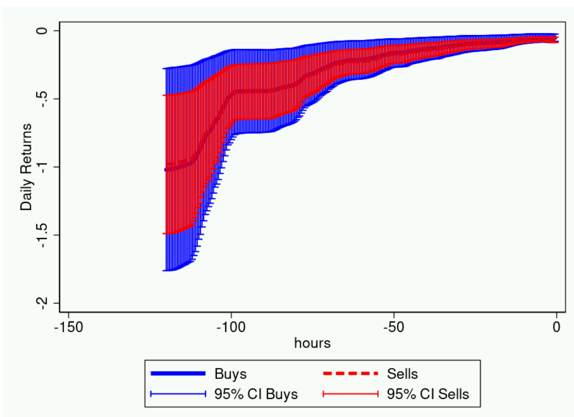
Figure 10. Trading Performance—Intra-Day Frequency



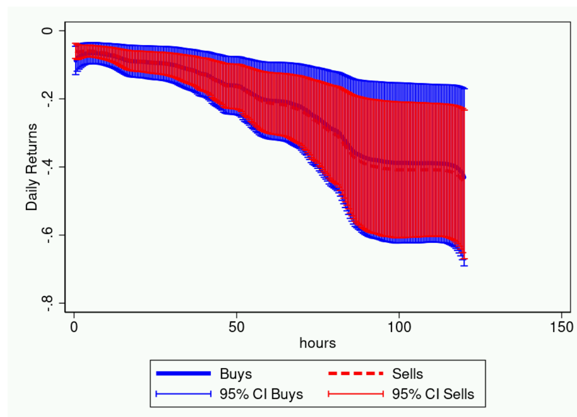
(a) Adjusted Returns in USD Before



(b) Adjusted Returns in USD After



(c) Adjusted Returns in USD Before



(d) Adjusted Returns in USD After

This plot reports the performance of cryptocurrencies before they are traded (left panels) and after they are traded (right panels) computed across only the trades of individual investors in the top two panels and institutional investors in the bottom two panels. The results are computed at the intra-daily frequencies and the buys are reported in blue while the sells are reported in red. The vertical bars represent 95% confidence intervals. The first row reports results for simple returns, the second for returns computed in US dollars, while the third reports results in US dollars, adjusted for the average return in US dollars of the top 10 traded cryptocurrencies.

Table 1. Facts Regarding Crypto Investors
Individual Investors

Panel A. Demographic Characteristics

	N	mean	sd	p1	p25	p50	p75	p99
Gender	172,802	0.64	0.48	0.00	0.00	1.00	1.00	1.00
Age	172,557	27.60	240.85	20.35	26.79	32.56	41.57	64.15

Panel B. Portfolio Characteristics

	N	mean	sd	p1	p25	p50	p75	p99
Num Assets	245,575	2.31	2.59	1.00	1.00	1.00	3.00	18.00
Total Value	245,575	274.69	37,156.66	0.00	0.00	0.01	0.94	781.55

Panel C. Attention Behavior (Monthly)

	N	mean	sd	p1	p25	p50	p75	p99
Login ALL	1,058,631	1.90	96.65	1.00	1.00	1.00	2.00	8.00
Login WEB	1,058,631	1.69	96.65	0.00	1.00	1.00	2.00	7.00
Login APP	1,058,631	0.09	0.58	0.00	0.00	0.00	0.00	2.00

Panel D. Trading Behavior

	N	mean	sd	p1	p25	p50	p75	p99
Total Trades	136,609	1,214.25	70,836.72	1.00	3.00	4.00	7.00	17,435
Total Volume ($)	136,609	723,008	154200000	1.73	21.75	27.72	67.83	279,928
Average Price ($)	136,609	53.95	1,726.03	0.00	0.04	0.07	0.14	630
User Horizon	136,609	1.45	1.95	1.00	1.00	1.00	1.00	12.13
Trades per month	136,609	448.18	12,740	1.00	3.00	4.00	6.00	12,055
Volume per month ($)	136,609	135,476	24,826,803	1.48	21.38	27.61	58.53	198,733

This table reports basic facts about cryptocurrency retail investors. Panel A reports information regarding their demographic characteristics, that is Gender and Age. Panel B reports Portfolio Characteristics—Number of assets held and Total portfolio value in USD—as of the last date available—April 2020. Panel C reports investors' monthly logins through all their devices, their desktop computer and their handheld devices, respectively. Finally, Panel D reports results on investors' trading activity: total trades, total volume in USD, average price of the cryptocurrency traded in USD, user trading horizon (in months), total trades per month and total volume per month (in US Dollars). For each variable, we report the number of investors used in the computation of the results, the average, standard deviation, as well as the first, 25th, 50th, 75th, and 99th percentile. The results in Panel C and D are computed by first computing time-series averages for each investor and then reporting the cross-sectional distribution.

Table 2. Facts Regarding Crypto Investors
Institutional Investors

Panel A. Demographic Characteristics

	N	mean	sd	p1	p25	p50	p75	p99
Gender	NA	NA	NA	NA	NA	NA	NA	NA
Age	NA	NA	NA	NA	NA	NA	NA	NA

Panel B. Portfolio Characteristics

	N	mean	sd	p1	p25	p50	p75	p99
N. Assets	88.00	3.89	4.43	1.00	1.00	2.00	4.00	19.00
Total Value	88.00	47,877	169,157	0.00	3.15	749.35	11,772.54	1,049,817

Panel C. Attention Behavior (Monthly)

	N	mean	sd	p1	p25	p50	p75	p99
Login ALL	261	3.88	3.94	1.00	1.88	2.75	4.33	19.89
Login WEB	261	3.61	3.68	1.00	1.67	2.44	4.00	19.43
Login APP	261	0.10	0.38	0.00	0.00	0.00	0.00	2.14

Panel D. Trading Behavior

	N	mean	sd	p1	p25	p50	p75	p99
Total Trades	69	151,835	433,640	1.00	34.00	189.00	4,877.00	2,508,305
Total Volume ($)	69	5,296,557	16,226,406	26.99	4,095.91	41,666	858,571	110,600,000
Average Price ($)	69	1,251	2,976.26	0.00	0.02	8.09	191.62	12,725
User Horizon	69	6.32	5.13	1.00	1.00	5.40	9.93	20.07
Trades per month	69	32,614	139,870	1.00	7.41	48.00	996.08	1,089,753
Volume per month ($)	69	1,757,443	6,689,025	26.99	803.05	13,507	95,717	38,900,364

This table reports basic facts about cryptocurrency institutional investors. Panel A reports information regarding their demographic characteristics, that is Gender and Age—which are not available for institutional investors. Panel B reports Portfolio Characteristics—Number of assets held and Total portfolio value in USD—as of the last date available—April 2020. Panel C reports investors' monthly logins through all their devices, their desktop computer and their handheld devices, respectively. Finally, Panel D reports results on investors' trading activity: total trades, total volume in USD, average price of the cryptocurrency traded in USD, user trading horizon (in months), total trades per month and total volume per month (in US Dollars). For each variable, we report the number of investors used in the computation of the results, the average, standard deviation, as well as the first, 25th, 50th, 75th, and 99th percentile. The results in Panel C and D are computed by first computing time-series averages for each investor and then reporting the cross-sectional distribution.

Table 3. Facts Regarding Crypto Investors

Market Makers

	Panel A. Demographic Characteristics							
	N	mean	sd	p1	p25	p50	p75	p99
Gender	NA	NA	NA	NA	NA	NA	NA	NA
Age	NA	NA	NA	NA	NA	NA	NA	NA
	Panel B. Portfolio Characteristics							
	N	mean	sd	p1	p25	p50	p75	p99
N. Assets	23.00	4.78	5.83	1.00	1.00	3.00	5.00	20.00
Total Value	23.00	10,838	19,838	0.01	10.10	757.68	12,976	74,191
	Panel C. Attention Behavior (Monthly)							
	N	mean	sd	p1	p25	p50	p75	p99
Login ALL	29.00	12.97	18.32	1.00	2.75	7.00	13.57	92.88
Login WEB	29.00	12.39	18.21	0.00	2.54	6.25	12.43	92.38
Login APP	29.00	0.26	0.35	0.00	0.00	0.00	0.50	1.00
	Panel D. Trading Behavior							
	N	mean	sd	p1	p25	p50	p75	p99
Total Trades	23	450,445	780,384	15.00	2,939.00	27,676.00	560,751.00	3,263,520
Total Volume ($)	23	190M	511M	1,733.35	412,634	6.071M	38.9M	1.93e+09
Average Price ($)	23	228	922.48	0.00	0.01	0.14	7.49	4,434
User Horizon	23	4.68	4.71	1.00	1.10	2.87	4.57	18.60
Trades Per Month	23	114,314	248,200	7.14	575	27,676	117,104	1,138,437
Volume Per Month ($)	23	38.4M	117.9M	380	126,980	1.5M	22,5M	549M

This table reports basic facts about cryptocurrency market makers. Panel A reports information regarding their demographic characteristics, that is Gender and Age—which are not available for market makers. Panel B reports Portfolio Characteristics—Number of assets held and Total portfolio value in USD—as of the last date available—April 2020. Panel C reports investors' monthly logins through all their devices, their desktop computer and their handheld devices, respectively. Finally, Panel D reports results on investors' trading activity: total trades, total volume in USD, average price of the cryptocurrency traded in USD, user trading horizon (in months), total trades per month and total volume per month (in US Dollars). For each variable, we report the number of investors used in the computation of the results, the average, standard deviation, as well as the first, 25th, 50th, 75th, and 99th percentile. The results in Panel C and D are computed by first computing time-series averages for each investor and then reporting the cross-sectional distribution.

Table 4. Top Cryptocurrencies and their Characteristics

Rank	Ticker	Name	Purpose	Release Year	Running Entity	Minable	CoinBase Rank
1	ETH	Ethereum	Blockchain Infrastructure	2015	Non-Profit	YES	2
2	ONT	Ontology	Blockchain Infrastructure	2018	Private Firm	NO	28
3	LTC	Litecoin	Currency	2011	Community	YES	8
4	EOS	EOS	Blockchain Infrastructure	2017	Private Firm	NO	12
5	XRP	XRP	Financial Services	2012	Private Firm	NO	4
6	BTC	Bitcoin	Currency	2008	Community	YES	1
7	FET	Fetch.ai	Computing & Data Storage	2019	Private Firm	NO	143
8	ZPR	ZPER	Financial Services	2018	Private Firm	NO	1,000
9	DASH	Dash	Currency	2014	Community	YES	25
10	ONG	Ontology Gas	Community Service	2018	Private Firm	—	2,097
11	ATLS	Atlas	Commerce & Retail	2019	Private Firm	NO	2,688
12	ABBC	ABBC Coin	Financial Services	2018	Private Firm	NO	83
13	WSC	WeSing Coin	Entertainment	2018	Private Firm	—	NA
14	NEO	NEO	Blockchain Infrastructure	2016	Private Firm	NO	21
15	BCHSV	Bitcoin Cash SV	Currency	2018	Community	YES	7
16	BUC	BuschCoin	Entertainment	2020	Private Firm	—	NA
17	TRX	Tron	Blockchain Infrastructure	2018	Non-Profit	NO	15
18	AIT	AIChain	Blockchain Infrastructure	2018	Private Firm	NO	1,189
19	BCHABC	Bitcoin Cash Abc	Currency	2018	Community	YES	5
20	BORA	BORA	Entertainment	2019	Private Firm	N	376

This table reports the ranking of the top cryptocurrencies over the full sample available 2018-2020, ranked by number of trades, and their major characteristics. Column 1 reports the ranking of the currency on the exchange we analyze; the second and third columns report the ticker and the name of the digital asset. The remaining column reports the purpose of the digital currency (column 4), the year the digital asset was released (column 5), the type of entity that issued the cryptocurrency (column 6), whether the cryptocurrency is minable (column 7), and the ranking of the cryptocurrency on CoinBase.

Table 5. Trading Behavior by Individual Investors — Top 4 Crypto Pairs

Panel A. ETH/BTC

	N	mean	sd	p1	p25	p50	p75	p99
Total Trades	8,015	1,159.95	39,323.04	1.00	1.00	3.00	68.00	18,467.00
Total Volume ($)	8,015	478,123.60	39709319	0.94	8.12	309.22	7,922.95	614,358.54
Average Price ($)	8,015	345.89	141.69	105.22	201.79	442.47	473.03	504.15
User Horizon	8,015	1.51	2.02	1.00	1.00	1.00	1.00	12.67
Trades Per Month	8,015	621.74	6,978.42	0.64	1.00	2.00	47.00	12,573.08
Volume Per Month ($)	8,015	98,957.93	6,697,005	0.90	8.07	236.97	6,010.64	422,089.75

Panel B. LTC/BTC

	N	mean	sd	p1	p25	p50	p75	p99
Total Trades	3,165	1,331.08	71,392.71	1.00	1.00	1.00	2.00	433.00
Total Volume ($)	3,165	985,513.80	53611303.00	0.70	11.95	13.83	20.98	20,697.53
Average Price ($)	3,165	120.62	24.03	44.68	114.46	122.31	137.08	157.60
User Horizon	3,165	1.10	0.88	1.00	1.00	1.00	1.00	5.20
Trades Per Month	3,165	238.52	12,379.98	1.00	1.00	1.00	2.00	426.00
Volume Per Month ($)	3,165	171,360.32	9,296,511.90	0.70	11.94	13.82	20.87	20,612.21

Panel C. XRP/ETH

	N	mean	sd	p1	p25	p50	p75	p99
Total Trades	1,453	7,973.55	74,878.30	1.00	1.00	5.00	6,341.00	32,662.00
Total Volume ($)	1,453	317,363.63	8,187,587.40	0.63	21.54	383.25	56,014.87	275,635.14
Average Price ($)	1,453	0.37	0.07	0.22	0.32	0.36	0.43	0.52
User Horizon	1,453	1.32	1.59	1.00	1.00	1.00	1.00	10.77
Trades Per Month	1,453	5,624.79	16,022.26	0.84	1.00	4.00	6,341.00	31,495.00
Volume Per Month ($)	1,453	89,937.90	1,470,424.20	0.63	19.79	319.04	54,462.70	262,380.66

Panel D. BCH/ETH

	N	mean	sd	p1	p25	p50	p75	p99
Total Trades	1,314	6,116.31	7,225.61	1.00	34.00	2,599.50	11,812.00	25,090.00
Total Volume ($)	1,314	72,904.86	77,029.85	12.46	7,348.62	43,929.70	118,667.57	254,023.81
Average Price ($)	1,314	669.47	112.77	501.02	576.25	644.99	787.41	869.74
User Horizon	1,314	1.03	0.25	1.00	1.00	1.00	1.00	2.80
Trades Per Month	1,314	6,055.49	7,207.84	1.00	34.00	2,158.39	11,724.00	25,090.00
Volume Per Month ($)	1,314	72,247.09	76,887.16	12.46	7,017.57	43,129.84	118,292.98	253,948.09

This table reports trading statistics for the most traded currency pairs: ETH/BTC, LTC/BTC, XRP/ETH and BCH/ETH. For each cryptocurrency pair and for each investor who trades it, we report the total number of trades over our sample, the total volume in dollars, the average price in dollars, the user horizons, the number of trades, and the dollar volume per month. For each quantity, we report the total number of investors the statistics are computed on, the average, standard deviation and 1st, 25th, 50th, 75th, and 99th percentiles of the distribution.

Table 6. Degree of Concentration in Trading (Herdindahl Index)

Currency	Spec 1	Spec 2	Spec 3	Spec 4
Market Maker	0.382	0.345	0.140	0.021
	(13.85)	(12.77)	(4.87)	(0.76)
Institutional Investor	0.431	0.397	0.264	0.215
	(8.93)	(8.40)	(5.28)	(4.43)
Total Trades		0.009	0.008	-0.001
		(45.22)	(39.75)	(-5.83)
Experience		-0.032	-0.033	-0.028
		(-58.51)	(-58.57)	(-51.16)
Trades per Month			0.076	0.078
			(51.98)	(55.42)
Volume per Month			-0.157	-0.190
			(-7.10)	(-8.89)
Total Logins			0.000	0.000
			(1.73)	(2.02)
Average US Price				0.006
				(9.10)
Trading Horizon				0.053
				(85.92)
Constant	0.081	0.044	0.049	0.078
	(147.67)	(55.03)	(56.53)	(86.56)
R-Square	0.002	0.044	0.069	0.127

This table reports results for cross-sectional regressions where the left-hand-variable is the normalized Herfindahl index of the stocks traded by investors, computed on the basis of the number of trades in each currency. The right-hand-side variables are, respectively, a dummy for whether a an investor is a market maker or an institutional investor (Spec 1); the total number of trades and the number of months on the platform (added in Spec 2); the total trades and volume per month and the total logins (added in Spec 3), the average US price of the cryptocurrency traded and the trading horizon in months (added in Spec 4). All the continuous variables regressions have been standardized.

Table 7. Number of Trades and Crypto Characteristics

	Spec 1	Spec 2	Spec 3	Spec 4	Spec 5
Minable	0.170				
	(80.19)				
Releaseyear		-0.049			
		(-63.62)			
CoinMarketCapRank			-0.035		
			(-54.74)		
Infrastructure				-0.004	
				(-1.33)	
Computation				-0.639	
				(-18.25)	
Entertainment				-0.073	
				(-23.23)	
Financial Services				-0.059	
				(-29.05)	
Other				-0.585	
				(-55.46)	
Community					0.105
					(51.05)
NonProfit					0.176
					(76.07)
Constant	1.339	1.423	1.430	1.478	1.355
	(1221.86)	(463089.80)	(36226.56)	(986.23)	(1588.25)
R-Square	0.724	0.719	0.717	0.730	0.722

This table reports results for panel regressions where the left-hand-variable is the number of trades placed by each investor in each cryptocurrency pair on the platform. Number of Trades is the natural logarithm of one plus total number of transactions that a user trades one cryptocurrency during the sample period (Panel A). The right-hand-side variables comprise a number of cryptocurrency characteristics. Minable is a dummy variable that equals one if this currency is minable, zero otherwise. Release Year is the release year of each currency. Currency, Infrastructure, Computation, Entertainment, Financial Services, and Others are dummy variables that equal one if the cryptocurrency is designed for the corresponding purpose, otherwise zero. The benchmark group is Currency, which contain those cryptocurrencies that are usually regarded as currency, e.g. Bitcoin, Litecoin, and Tether. Community, NPO, and Private are dummy variables that indicate whether a cryptocurrency is issued and maintained by the community (e.g. Bitcoin), non-profit organization (e.g. Ethereum), or private company (e.g. Tether). The benchmark group is Private. CoinMarketCap Rank is the trading volume ranks of cryptocurrencies as of Sept 30, 2020. All continuous variables, namely, Release Year and CoinMarketCap Rank, have been standardized. We include user fixed effects in all specifications. We also report t-statistics in the parentheses with standard errors clustered at user level.

Table 8. Average Trade Horizon and Crypto Characteristics

	Spec 1	Spec 2	Spec 3	Spec 4	Spec 5
Minable	0.012				
	(7.73)				
Releaseyear		-0.004			
		(-6.72)			
CoinMarketCapRank			0.000		
			(0.27)		
Infrastructure				-0.017	
				(-7.42)	
Computation				-0.075	
				(-1.69)	
Entertainment				0.010	
				(3.47)	
Financial Services				0.006	
				(4.03)	
Other				0.046	
				(3.43)	
Community					0.009
					(5.13)
NonProfit					0.003
					(1.42)
Constant	0.276	0.295	0.284	0.295	0.292
	(333.53)	(417831.11)	(6411.96)	(244.96)	(425.61)
R-Square	0.808	0.810	0.807	0.810	0.810

This table reports results for panel regressions where the left-hand-variable is the average horizon of return trades (trades in opposite direction) placed by each investor in each cryptocurrency on the platform, measured in days. The right-hand-side variables comprise a number of cryptocurrency characteristics. Minable is a dummy variable that equals one if this currency is minable, zero otherwise. Release Year is the release year of each currency. Currency, Infrastructure, Computation, Entertainment, Financial Services, and Others are dummy variables that equal one if the cryptocurrency is designed for the corresponding purpose, otherwise zero. The benchmark group is Currency, which contain those cryptocurrencies that are usually regarded as currency, e.g. Bitcoin, Litecoin, and Tether. Community, NPO, and Private are dummy variables that indicate whether a cryptocurrency is issued and maintained by the community (e.g. Bitcoin), non-profit organization (e.g. Ethereum), or private company (e.g. Tether). The benchmark group is Private. CoinMarketCap Rank is the trading volume ranks of cryptocurrencies as of Sept 30, 2020. All continuous variables, namely, Release Year and CoinMarketCap Rank, have been standardized. We include user fixed effects in all specifications. We also report t-statistics in the parentheses with standard errors clustered at user level.

Table 9. Individual Investor Portfolio Returns

Panel A. Daily Frequency

	N	mean	sd	p1	p25	p50	p75	p99
Mean Return	471,624	-0.01	0.05	-0.11	-0.02	-0.00	0.00	0.05
Mean Excess Return	471,624	-0.01	0.05	-0.10	-0.01	0.00	0.01	0.06

Panel B. Monthly Frequency

	N	mean	sd	p1	p25	p50	p75	p99
Mean Return	359,360	-0.02	0.20	-0.77	-0.08	0.00	0.06	0.30
Mean Excess Return	359,360	0.03	0.22	-0.43	-0.08	0.01	0.08	0.63

Panel C. CAPM Regressions at Daily Frequency

	N	mean	sd	p1	p25	p50	p75	p99
Alpha Estimate	296,713	0.01	0.02	-0.02	-0.00	0.00	0.00	0.06
Alpha T-statistic	296,641	0.57	1.34	-2.28	-0.44	0.93	1.41	2.76
Beta Estimate	296,710	0.73	0.32	0.21	0.54	0.62	0.76	1.59
Beta T-statistic	296,641	12.90	8.44	0.44	5.08	12.16	17.20	28.25

Panel D. CAPM Regressions at Monthly Frequency

	N	mean	sd	p1	p25	p50	p75	p99
Alpha Estimate	266,403	0.00	0.09	-0.19	-0.04	0.01	0.03	0.17
Alpha T-statistic	266,386	-0.01	1.34	-3.31	-0.82	0.12	1.15	1.84
Beta Estimate	266,403	0.59	0.29	-0.06	0.46	0.54	0.69	1.17
Beta T-statistic	266,386	4.05	2.78	-0.19	1.79	3.08	6.47	9.63

This table reports, in Panel A, individual portfolios average daily returns as well as daily returns in the excess of a cryptocurrency benchmark—the average return on the 10 most traded cryptocurrencies. Panel B reports similar statistics at the monthly frequency. Panel C and Panel D report CAPM regressions at the daily and monthly frequencies, respectively, where the market portfolio is the average return on the 10 most traded cryptocurrencies. For every quantity reported in the table, we report the number of users associated with each statistic, as well as the cross-sectional mean and standard deviation. Finally, we report the 1st, 25th, 50th, 75th and 99th percentile of the distribution.

Table 10. Explaining the Cross-section of Portfolio Returns

	Alpha t-Stat	Exc. Ret.	Alpha t-Stat	Exc. Ret.
Total Logins	0.165	0.051	0.036	0.029
	(51.36)	(55.41)	(6.00)	(14.71)
Trades per Month	-0.163	-0.079	-0.173	-0.059
	(-39.17)	(-66.26)	(-28.65)	(-30.37)
Number of Assets	0.079	0.086	-0.059	-0.021
	(22.17)	(84.82)	(-8.57)	(-9.69)
Portfolio Value	-0.017	-0.001	-0.069	-0.016
	(-5.17)	(-1.41)	(-14.30)	(-10.36)
Institutional Investors	-0.230	0.109		
	(-1.61)	(2.66)		
Age			-0.018	-0.008
			(-22.20)	(-32.27)
Male			-0.039	0.010
			(-2.28)	(1.87)
Constant	-0.191	-1.625	1.169	-1.082
	(-45.70)	(-1359.94)	(35.00)	(-101.00)
R-Square	0.022	0.069	0.087	0.101

This table reports cross-sectional regressions of investor performance. The dependent variable is the Alpha t-statistic in columns 1 and 3 and the returns in excess of the average return on the top 10 cryptocurrencies in columns 2 and 4. Regressors include the total number of logins, an institutional investor dummy, the number of trades per month, the total number of assets and the value of the portfolio. Columns 3 and 4 remove the institutional investor dummy and add the investors age, as well as a Male dummy.

Online Appendix for the Paper:

(Not for publication)

Table Online I. Facts Regarding Crypto Investors
All Investors

Panel A. Demographic Characteristics

	N	mean	sd	p1	p25	p50	p75	p99
Gender	172,923	0.64	0.48	0.00	0.00	1.00	1.00	1.00
Age	172,678	27.56	241.06	20.35	26.79	32.56	41.57	64.15

Panel B. Portfolio Characteristics

	N	mean	sd	p1	p25	p50	p75	p99
Num Assets	245,867	2.31	2.59	1.00	1.00	1.00	3.00	18.00
Total Value	245,867	329.18	37,929.80	0.00	0.00	0.01	0.95	839.89

Panel C. Attention Behavior (Monthly)

	N	mean	sd	p1	p25	p50	p75	p99
Login ALL	1,059,186	1.90	96.63	1.00	1.00	1.00	2.00	8.00
Login WEB	1,059,186	1.69	96.62	0.00	1.00	1.00	2.00	7.00
Login APP	1,059,186	0.09	0.58	0.00	0.00	0.00	0.00	2.00

Panel D. Trading Behavior

	N	mean	sd	p1	p25	p50	p75	p99
Total Trades	136,747	1,290	71,538	1.00	3.00	4.00	7.00	17,640
Total Volume ($)	136,747	724,957	154,100,000	1.73	21.76	27.73	68.70	284,725
Average Price ($)	136,747	54.85	1,727	0.00	0.04	0.07	0.14	637
User Horizon	136,747	1.45	1.96	1.00	1.00	1.00	1.00	12.17
Trades per month	136,747	464.34	13,130	1.00	3.00	4.00	6.00	12,208
Volume per month ($)	136,747	136,230	24814748	1.47	21.39	27.61	59.18	200,605

This table reports basic facts about cryptocurrency investors. Panel A reports information regarding their demographic characteristics, that is Gender and Age. Panel B reports Portfolio Characteristics—Number of assets held and Total portfolio value in USD—as of the last date available—April 2020. Panel C reports investors' monthly logins through all their devices, their desktop computer and their handheld devices, respectively. Finally, Panel D reports results on investors' trading activity: total trades, total volume in USD, average price of the cryptocurrency traded in USD, user trading horizon (in months), total trades per month and total volume per month (in US Dollars). For each variable, we report the number of investors used in the computation of the results, the average, standard deviation, as well as the first, 25th, 50th, 75th, and 99th percentile. The results in Panel C and D are computed by first computing time-series averages for each investor and then reporting the cross-sectional distribution.