Are Cryptos Different? Evidence from Retail Trading*

Shimon Kogan† Reichman University and Wharton

Igor Makarov‡ LSE

Marina Niessner§ Wharton

Antoinette Schoarl ¶ MIT

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Abstract

Cryptocurrenices are growing in importance and unlike other nascent asset classes, they are dominated by retail investors. Despite that, little is know about the determinants of retail trading in cryptocurrencies. We utilize a large dataset of retail traders from eToro, one of the first retail brokers to introduce cryptocurrecy trading. Studying the behavior of over 200,000 individuals, we show that retail traders have a different model of the underlying price dynamics in cryptocurrencies compared to stocks. Retail traders in our sample are contrarian in stocks and in gold, yet same traders follow a (passive) momentum strategy in cryptocurrencies. Lack of cashflow information, inattention, or preference for lottery-like stocks do not explain the trading behavior in cryptocurrencies in our data.

Keywords: Cryptocurrencies, FinTec, Retail trading, Social finance

JEL Codes: G41, G12, G14

*We thank eToro for graciously providing their data. All remaining errors are our own.

†Arison School of Business, Reichman University, and the Wharton School. Email: skogan@wharton.upenn.edu

‡London School of Economics. Email: i.makarov@lse.ac.uk

§University of Pennsylvania. Email: niessner@wharton.upenn.edu

¶Sloan School of Business, MIT. Email: aschoar@mit.edu

1. Introduction

Cryptocurrency prices over the last decade have famously been marked by significant volatility and large boom and bust cycles, which has even coined new terms such as FOMO — "fear of missing out" or FUD — "fear, uncertainty and doubt". Over the same period, cryptocurrencies have gained increasing interest, especially from retail investors, yet little evidence exists on the way retail investors trade in this new the asset class. Specifically, is there something special in how investors trade and update price expectations about cryptocurrencies compared to other assets? Or are potential differences between crypto and other assets driven by heterogeneity in the types of retail investors who are attracted to such speculative assets?[1]

To answer these questions, we use a dataset of trades from more than 200,000 individual retail accounts from eToro, a large international discount brokerage, over the period from 2015-2019. eToro has been one of the first platforms to allow retail investors to trade in cryptocurrencies along with traditional assets. We document a set of new facts by contrasting trading in cryptocurrencies versus stocks and commodities. We show a stark dichotomy in investors' trading strategies across different assets. Retail investors largely trade as contrarian in the stock market but they follow momentum strategies when trading in crypto currencies. These results hold even when we focus on the same investors trading across these different assets. In contrast, other individual characteristics are much less important in explaining differences in how people trade in cryptocurrencies versus stocks.

To analyze how investors form price expectations we look at the portfolio share that an investor holds within a given stock or cryptocurrency and how it changes as a function of the contemporaneous and lagged returns on the asset. This approach is similar to Calvet et al. (2009), which ties changes in portfolio shares allocated to different *asset classes* to their beliefs about asset class returns. We extend the Calvet et al. (2009) framework to allocations across individual stocks and cryptocurrencies based on a few simple assumptions. Following Campbell et al. (2002), and the assumptions therein, we show, theoretically, that changes in the portfolio weights on different stocks or cryptocurrencies are driven by changes in the expected returns. Thus if investors expect next period returns to be positively correlated with this period's returns, we expect that following a positive (negative) return of a stock or cryptocurrency, investors will allocate a larger (smaller) share of their wealth to this stock. And vice versa if investors expect stocks to be mean-reverting. If investors continuously pay attention to their portfolio and re-balance in response to changes in their beliefs, the sign of the change in the *total portfolio share* of an asset regressed on its contemporaneous or past return at any point in time reflects

[1] The recent Meme stock mania has shown that a subset of retail investors seems to be attracted in particular to skewness in returns and lottery like stocks.

how investor's price expectation as a function of price realizations.

We implement this analysis by regressing the change in the portfolio share of a given asset on the current day's log return and control for lagged cumulative weekly returns for the five prior weeks. We focus on the 200 most traded stocks on our retail platform, which comprise more than 91% of trading in stocks. There are a number of different cryptocurrencies that investors can trade on the platform, but the majority of capital, during our sample period, is concentrated in a few dominant tokens, in particular Bitcoin, Ethereum and Ripple.

One feature of retail investor trading is that many people only trade sporadically and might stay in the market or exit it for reasons unrelated to their investment believes, possibly maybe because they are distracted or inattentive. As a result, individual account-level portfolio share change analysis is subject to a lot of spurious noise when related to response to daily price changes. To deal with this problem, we form our measure of portfolio shares, aggregated at the cohort level. If some investors stay out of the market for random reasons that are driven by idiosyncratic drivers, our aggregation strategy will reduce the noise introduce by them. However, any changes in investment behavior that are related to fundamentals, or prices which broadly affect investors in a given cohort, will of course be picked up by our measure. We also repeat the analysis at the individual level by looking at buy and sell decisions of individuals in response to contemporaneous and lagged returns. The results confirm our analysis at the cohort level.

We find that for stocks, there is a significant and negative relationship between the change in the share that is allocated to a given stock and its contemporaneous return. Lagged cumulative returns one week out have still a negative but much weaker relationship to portfolio shares, and returns do not have a significant impact beyond one week. When we repeat the same analysis for cryptocurrencies, we find a strong positive relationship between the total share allocated to cryptocurrencies and the contemporaneous returns. We again find a much weaker but still positive relationship for cumulative lagged returns one week out. In other words, investors are momentum traders in cryptocurrencies but contrarian in stocks.

We then follow Calvet et al. (2009) and break out the total change in the portfolio shares into the passive and the active shares. The active share constitutes the part of the change in the total share that is due to an investor actively rebalancing their portfolio allocation. The remainder is the passive share, which is the result of differential asset returns over time. For example, take a stock that appreciates more than the rest of the assets in the portfolio over a given time period. If the investor does not actively re-balance the portfolio, this stock will increase its share in the portfolio over time. For an attentive investor the important statistic is the net change in the total share, since it reflects

the investor's allocation after taking into account the passive price changes. But since investors might not always we perfectly attentive to price changes, it is informative to analyze how active re-balancing interacts with passive changes in the porfolio due to price changes.

We find that the contrarian trading behavior that we observe for stocks is due to investors actively reducing their portfolio holdings in stocks that had high contemporaneous returns, and vice versa for negative returns. Parallel to what we found for the total share, the re-balancing effects are much weaker for one-week lagged cumulative returns. However, for crypto holdings we see that the momentum behavior are predominantly driven by investors not actively re-balancing their holdings in crypto currencies, whether the price goes up or down. So retail investors are willing to passively absorb these price swings without adjusting their portfolios.

We also repeat this analysis for trading in commodities, in particular gold, which often draws parallels to Bitcoin, and is one of the two most traded commodities on eToro. [2] We find that investments in gold follow the same contrarian dynamics as stocks. Investors reduce their total holdings and actively rebalance out of gold when the price of gold increases and vice versa for price declines. Since cryptocurrencies have often been touted as the *digital gold*, it is interesting to see the stark difference in trading behaviors between gold and crypto. This finding confirms that cryptocurrencies are special, at least from the perspective of retail investor trading. And the narrative that crypto is the new gold does not seem to apply.

To test if these results are driven by days with extreme realizations in the different assets, we classify trading dates for each asset into return quintiles, from the lowest to the highest and repeat our analysis for stocks, gold and cryptocurrencies. We find that the contrarian trading in stocks and gold is particularly concentrated on days when there are large price movements, either positive or negative. The effect is much smaller on interim-return days. In contrast, for cryptocurrencies, we find no change in active re-balancing as a function of the return quintile. In other words, investors do not re-balance even after very large price movements and absorb the price changes.

One important question that arises from these results is whether the stark difference in trading patterns is asset specific or a function of investor self-selection, where retail investors with contrarian trading strategies predominantly invest in stocks and momentum traders in cryptocurrencies. We can rule out the self-selection hypothesis, since we observe investors who trade in both stocks and crypto, and those who trade in only one of them. Investor who invests in both, stocks and cryptocurrencies, display the same momentum strategy in cryptocurrencies as someone who only trades in crypto. But

[2] The other popular commodity is oil, but the pricing of oil is more complicated since there are many potential prices investors might react to and therefore it does not lend itself to the same analysis we conduct here.

investors who invests in both, follows contrarian strategies when trading in stocks. In fact, investors who only invest in stocks, tend to be slightly less contrarian in stocks than investors who invest in both. This is in particular driven by periods of negative returns, when the stock-only investors seem to take money out of the market. In short, we confirm that the dichotomy in trading behavior even holds *within* a given person and thus is asset specific.

One might wonder if a few subgroups of traders that are particularly optimistic about crypto, say younger or financially savvy people, are driving the momentum strategies in cryptocurrencies. Our findings show that there is only very limited heterogeneity in trading behavior across investor types: we test if the relationship between portfolio shares and returns differs with the personal characteristics of the traders. The dimensions we focus on are age, wealth, income, whether the first trade on the platform someone made was in stock or crypto, whether they work in the finance industry and others. Surprisingly, we do not find strong interactions between ex-ante characteristics and belief updates. The dichotomy in trading strategies, where investors are contrarian in stocks but momentum in cryptocurrencies is preserved independent of people's characteristics.

The one group of traders that displays slightly different trading behavior are so called "Guru traders" on the platform. These are a subset of traders who are white-listed by the platform to allow other users to automatically copy their trades. That is, once someone becomes a Guru, other investors can sign up to follow the Guru's portfolio choices and trade along with them. We see that Gurus tend to be a bit more contrarian in their trading strategies. This is true for stocks as well as for crypto currencies. But it is difficult to differentiate if Guru's tend to be more contrarian since they have a different model of returns from regular retail investors. Or if Gurus have a more complex set of objectives, since they get paid for the trades they generate. Thus, they might not only want to maximize returns but possibly also trade very actively if this entices other retail investors to follow them.

A complication arises if investors do not pay attention to their portfolio continuously. In this case, the portfolio share of an asset can at times increase (decrease) mechanically following positive (negative) returns. Thus, to link our results to expectations we focus on times when we investors are likely to pay attention to their portfolio. Here, analyzing changes in the active share allows us to condition on periods where we know investors actively engage with their portfolio to see if these allocation changes are in line with the passive changes or reverse them.

When we classify investors as *active* or attentive, if they traded at least once (any asset) in the last month, we see no significant difference to inactive investors: The dichotomy in stocks and cryptocurrencies is still very strong, with crypto investments following a momentum strategy and stock investments a contrarian strategy. Even when we condition active as having traded both cryptocurrencies and stocks

at least once in the last month, we find that even when the crypto investors rebalance a bit as a function of returns, they do not undo the momentum in the total portfolio share. These results suggest that the measured changes in total portfolio shares are an expression of investor updating about prices and not just passively riding out price movements. In addition, it is difficult to argue that investors in our sample are generally inattentive and passive. We see that the same investors who are trading actively in stocks and counter-cyclically re-balancing, holds on to their cryptoinvestments overtime.

These results suggest that investors apply a different model when updating about the price of cryptocurrencies than for other assets. In stocks investors seem to believe that once the price has gone up or down, it is likely that the price will mean revert. But for cryptocurrencies an increase in prices seems to confirm investors believe that prices should go up even more (and parallel on the downside).

In the second part of the paper, we shed more light on the underlying channels that drive these difference in trading behavior between cryptocurrencies and stocks. Cryptocurrencies are an entirely new investment vehicle, whose future value to a large extent depends on investors' beliefs about whether there will be wider market adoption going forward. Thus investors might use price movements as an indicator of future adoption. If the likelihood of adoption increases when the price goes up, say because regulators or institutional investors now look more favorably at cryptocurrencies, these price movements can have an amplification effect. This type of belief structure could explain the momentum trading behavior displayed among our retail investors.

But there are also a number of alternative channels that could explain retail trader behavior in cryptocurrencies. First, one might hypothesize that cryptocurrencies have only been around for a short period and thus investors had never experienced a crash in prices and mainly observed positive returns. But within our sample period we observe one large crash in cryptocurrencies, at the beginning of 2018. When comparing the regressions of total portfolio change on returns for the periods before and after the 2018, we see a slight dampening of the sensitivity of portfolio shares on returns, but overall the relationship is still strongly positive. When repeating the same analysis for the active share, we see a small change in active portfolio adjustments after the 2018 crypto crash, where investors are reblancing after strong price movement. But overall these are very small adjustments which do not change the overall momentum trading in crypto.

A second candidate explanation is that investors might be willing to invest in lottery like assets differently than other types of securities. Therefore, we analyze if trading in stocks that have very skewed of lottery-like returns follows a similar pattern to cryptocurrencies. We first classify stocks into lottery-like returns following the approaches of Bali et al. (2021) and Han et al. (2022). We use five different ways to classify lottery stocks, maximum returns in the prior year, volatility of returns,

skewness, firms that had an IPO less than a year ago, and GMA. We then repeat the same estimation model as above but interact the contemporaneous log returns with measures of the lottery-likeness of firm returns over the prior year. We find that investors follow a slightly less contrarian strategy in stocks that are more lottery like, as measured by max return by month or return volatility. But the effect is small and only borderline significant. In addition, when using the three remaining classification of lottery stocks: skewness, less than 1-year from IPO and GMA, we do not see any effect. This suggests that retail investors do not just react to the lottery like features of cryptocurrency returns. If that was the case, we should see similar behaviors for the most lottery like stocks as well.

Third, one might wonder if the lack of periodic cash flow information about cryptocurrencies explains the difference to stocks. Luo et al. (2020) suggest that earnings announcement dates provide retain investors with periodic events to reevaluate their beliefs about the valuation of stocks. Retail investors and seem to believe that other investors are overly optimistic or pessimistic about prices, which induces them to trade contrarian around those dates. The same is not possible for cryptocurrencies, where investors do not receive any cashflow news. We confirm that similar to the findings in Luo et al. (2020), the contrarian trading behavior for stocks is especially strong around earnings announcement dates in our data as well. When we split the sample of stock trades between earnings announcement dates and the rest, we see that a large fraction of the effect comes from these specific earnings announcement dates. But the lack of cashflow information cannot be the full story in explaining our findings, since we also find contrarian trading in gold, where, similar to cryptocurrencies, investors do not receive cashflow information.

In sum, our results suggest that investors have a different model of the underlying price dynamics in cryptocurrencies compared to stocks. Retail traders in our sample are contrarian in stocks, especially around earnings announcement dates, in line with what prior studies in this literature have found. But these same traders follow a (passive) momentum strategy in cryptocurrencies. Lack of cashflow information, inattention or preferences for lottery like stocks do not explain the trading behavior in cryptocurrencies. Instead, it seems either investor sentiment follows a dynamic where investors turn positive or negative on cryptocurrencies in a very correlated fashion, and thus our investors buy (sell) more when prices go up (down). But it might also be a sign of a more complex updating, if investors think that the price of cryptocurrencies also affects the likelihood of future adoption of cryptocurrencies in the economy. Given such a model it would be rational to become more optimistic about crypto currencies when the price goes up. In short, in investors' minds cryptocurrencies are indeed different.

2. Model

The goal of the model is to provide a framework that ties investors' asset allocation choices with their return beliefs over these assets. Through this section, we will use the following notations:

- X_t^i — Number of shares of asset i held at time t
- P_t^i — Price of asset i at time t
- W_t — Wealth at time t
- $w_t^i = \frac{X_t^i P_t^i}{W_t}$ — Share of asset i

When there is only one risky asset and a riskless asset, Campbell et al. define the passive risky share as

$$w_{p,t+1} = \frac{w_t(1 + r_{t+1})}{w_t(1 + r_{t+1}) + (1 - w_t)(1 + r_{t+1}^f)}, \tag{1}$$

where $1 + r_{t+1} = \frac{P_{t+1}}{P_t}$ and r_f is the return on the riskfree asset. Suppose that the portfolio is rebalanced only at discrete times t, $t + 1$, etc. Notice that we can rewrite the passive risky share as

$$w_{p,t+1} = \frac{X_t P_{t+1}}{X_t P_{t+1} + (W_t - X_t P_t)(1 + r_{t+1}^f)} = \frac{X_t P_{t+1}}{W_{t+1}}. \tag{2}$$

In our case, we generalize this definition to the case of N risky assets as:

$$w_{p,t+1}^i = \frac{X_t^i P_{t+1}^i}{X_t^i P_{t+1}^i + (W_t - X_t^i P_t^i)(1 + r_{t+1}^{-i}) + Inflows} = \frac{X_t^i P_{t+1}^i}{W_{t+1}}. \tag{3}$$

The active change in the risky share is then

$$A_{t+1}^i = w_{t+1}^i - w_{p,t+1}^i = \frac{X_{t+1}^i P_{t+1}^i}{W_{t+1}} - \frac{X_t^i P_{t+1}^i}{W_{t+1}} = \Delta X_{t+1}^i \frac{P_{t+1}^i}{W_{t+1}}, \tag{4}$$

In logs, we can write out the change in portfolio shares as:

- Active share change

$$a_{t+1}^i = \ln(w_{t+1}^i) - \ln(w_{p,t+1}^i) = \ln(X_{t+1}^i) - \ln(X_t^i). \tag{5}$$

- Total share change

$$\ln(w^i_{t+1}) - \ln(w^i_t) = \ln\left(\frac{X^i_{t+1}P^i_{t+1}}{W_{t+1}}\right) - \ln\left(\frac{X^i_t P^i_t}{W_t}\right) = a^i_{t+1} + \ln\left(\frac{P^i_{t+1}}{P^i_t}\right) - \ln\left(\frac{W_{t+1}}{W_t}\right). \quad (6)$$

Portfolio policy:

Assumption 1. Investors have power utility function and follow myopic portfolio policy.

The assumption of power utility function is quite standard. Myopic portfolio policy eliminates the need to consider hedging demand. While there is an extensive literature discussing the importance of inter-temporal considerations, such as when using an Epstein-Zin utility, in our setting inter-temporal considerations are likely to have first order importance as most trades in our data have short horizon.

Under Assumption 1, it is well known (e.g., Campbell and Viceira 2001), that the vector of optimal portfolio weights is

$$w_t = \frac{1}{\gamma}\mathbf{\Sigma_t^{-1}}(E_t\mathbf{r_{t+1}} - r_f\mathbf{1} + \mathbf{\sigma_t^2}/2), \quad (7)$$

where $\Sigma_t = Cov_t(\mathbf{r_{t+1}}, \mathbf{r_{t+1}})$ and $\sigma^2_t = Var_t(\mathbf{r_{t+1}})$. The above formula shows that the portfolio weights can change either if the first or second moments change.

Assumption 2. Σ_t is constant.

Assumption 2 implies that changes in the portfolio weights are driven by changes in the expected returns and not by changes to the covariance across assets over time. The persistence of variance (and covariance) implies that, over short time intervals, changes in first moments would be more pronounced than changes to second moments. In our empirical setting, the analysis is based on daily changes in portfolio shares and thus the assumption is likely to hold approximately.

It is natural to think that when investors have more optimistic beliefs about the expected return on a stock the weight of this stock in their portfolio goes up, and the weights of other stocks decline. The next proposition provides sufficient conditions for this property to hold.

PROPOSITION 1. *Suppose Assumptions 1 and 2 hold and suppose stocks follow a one-factor model:*

$$r^i_{t+1} = E_t r^i_{t+1} + \beta_i f_{t+1} + \varepsilon^i_{t+1}, \quad (8)$$

$$\beta_i > 0, \quad E_t f_{t+1}\varepsilon^i_{t+1} = 0, \quad E_t\varepsilon^i_{t+1} = 0, \quad E_t\varepsilon^i_{t+1}\varepsilon^j_{t+1} = 0, \quad \textit{for} \quad i \neq j. \quad (9)$$

Then

$$\frac{\partial w_t^i}{\partial E_t r_{t+1}^i} > 0, \tag{10}$$

$$\frac{\partial w_t^i}{\partial E_t r_{t+1}^j} < 0. \tag{11}$$

Proof: Denote $Var_t(f_{t+1})$ by σ^2 and $Var_t(\varepsilon_{t+1}^i)$ by σ_i^2. Then

$$\Sigma_{ij} = \begin{cases} \beta_i \beta_j \sigma^2, & \text{for} \quad i \neq j \\ \beta_i^2 \sigma^2 + \sigma_i^2, & \text{for} \quad i = j. \end{cases} \tag{12}$$

Let $\mathbf{x}$ be a vector with elements $x_i = \beta_i \sigma$. Denote a diagonal matrix with elements σ_i^2 by D. Then we can write Σ as

$$\Sigma = D + \mathbf{x}\mathbf{x}'. \tag{13}$$

Using the Sherman–Morrison formula we have

$$\Sigma^{-1} = (D + \mathbf{x}\mathbf{x}')^{-1} = D^{-1} - \frac{D^{-1}\mathbf{x}\mathbf{x}'D^{-1}}{1 + \mathbf{x}'D^{-1}\mathbf{x}}. \tag{14}$$

Thus,

$$\Sigma_{ij}^{-1} = \begin{cases} -\frac{\beta_i \beta_j}{\sigma_i^2 \sigma_j^2 \left(\sigma^{-2} + \sum_j \beta_j^2 / \sigma_j^2\right)} < 0, & \text{for} \quad i \neq j \\ \frac{\sigma^{-2} + \sum_{j \neq i} \beta_j^2 / \sigma_j^2}{\sigma_i^2 \left(\sigma^{-2} + \sum_j \beta_j^2 / \sigma_j^2\right)} > 0, & \text{for} \quad i = j, \qquad Q.E.D. \end{cases} \tag{15}$$

An important question is how investors form their expectations of $E_t \mathbf{r_{t+1}}$.

Assumption 3. Investors use past returns to update their expectations of future returns as follows

$$corr(E_t r_{t+1}^i, r_t^i) = \rho. \tag{16}$$

Remark. Assumption 3, together with Proposition 1, implies that following a positive(negative) return of stock i investors will be willing to allocate a larger(smaller) share of their wealth to this stock (it is arguably a strong assumption, which does not hold in all models). We can test this implication by regressing the total share change on past return. One complication arises if investors do not pay attention to stocks all the time and thus fail to optimize their portfolios. In this case, the stock share

in the portfolio can increase mechanically following a positive(negative) return.

If investors always pay attention and thus rebalance their portfolio in response to changes to their beliefs then the sign of the regression of the total share change on the past return should coincide with the sign of ρ. Notice that the role of the active share change in this case is secondary. In particular, it can be the case that $\rho > 0$, the sign in the total share change regression is positive, and the sign in the active share change regression is negative (after controlling for everything else).

If investors do not always pay attention to what is going in the marker then the positive sign in the total share change regression might be consistent with limited attention. In this case, to link our results to expectations we need to focus on the times when we know investors are likely to pay attention. These could be times when investors trade. Notice, again that conditional on the fact that investors trade, the role of the active share change in this case is secondary — the main statistics is the total share change.

3. Data

Our data comes from eToro, a global brokerage platform founded in 2007 that serves, as of July 2022 over 30M users, with 2.7M funded accounts, in more than 100 countries.[3] It allows users to trade in a wide array of assets classes including currencies, commodities, equity indexes (and individual equities, primarily large companies), as well as in more recent years, crypto currencies. Trades are often implemented through CFDs ("contract for difference"), which is essentially a derivative contract on the underlying asset with cash settlement. The use of these contracts allows the eToro to implement trades that are small in size and across a large number of assets. It also allows users to take on trade-specific leverage.

Our unique dataset allows us a view into characteristics of the retail trader (e.g., age, gender, country of residency, and self-claimed financial proficiency), all their trades (time-stamped), and their portfolio daily balance across different asset classes. eToro allows users to initiate direct trades as well as "copy" trades of other users by selecting to follow them. In this paper, we focus on self initiated trades in stocks, crypto currencies, and commodities. Our data spans the period 1/1/2015 through 12/15/2019. [4] As Fig 1 shows, in line with the price appreciation in crypto currencies, eToro experienced strong growth in cryptocurrency trading beginning mid 2016. By the end of 2017, when cryptocurrency prices reached a peak, the share of dollar amounts invested in cryptocurrencies accounted for over 85% of all trading volume among the users in our sample. When the price dropped at the beginning of 2018, amount of dollars invested in cryptocurrencies also declined and stabilized around 20% of total investments

[3] See https://www.etoro.com/about/investors/

[4] eToro shared with us data on users who, at any point in time, followed at least one guru.

made on eToro. A very similar shift toward crypto currency trading is observed, albeit during a later period, in other retail trading venues such as Robinhood (as of 9/31/2021, Robinhood's transaction-based revenues from equities and crypto currencies were nearly identical [5]). As Figure 1 shows, besides stocks and crypto, retail traders on eToro also trade in commodities, foreign exchange and equity indices. The volume of currency trades was quite high on the platform early on, reaching almost 70% at the beginning of 2015, but steeply declined over the next two years and by 2017 the volume of trades dropped to around 10% and stayed at this level. In contrast, the volume of commodity trades increased slightly over the time period, from about 10% of volume in 2015 to around 25% by the end of 2019. The majority of commodity trades are comprised of gold and oil. We will focus our analysis of trading behavior on crypto, stocks and commodities, and within commodities on gold, especially in light of the narrative that draws paralles between crypto currencies and gold. We will abstain from looking at currency trades, since trading in forex has been relatively small since 2017, but most importantly given the international nature of the eToro platform, it is difficult to know how much of these trades are for investment and speculative purposes and how much might be to hedge real currency exposures.

Table 1 provides summary statistics for the users in our sample. Panel A reports characteristics for the over 200,000 traders we observe in the data. These traders traded on average 80 times during their average account duration of 1.2 years (or a trade every 5.6 days, on average). The average user traded 14 different stocks and 2 different cryptocurrencies. Roughly half of the users were new to trading when they joined the platform (i.e., had less than a year of experience), were young (under 35 years of age), and had low liquid wealth (i.e., less than $10,000). Only 20% of the users indicated that they had professional background in finance.

Panel B reports the daily returns statistics for the assets we study, during our sample period. The average daily return in the sample is zero for the top 200 stocks traded on eToro and also zero for gold, but slightly positive for crypto currencies, with a mean daily return of 0.002. The standard deviation of daily returns is also much higher for crypto currencies (0.053) comapred with stocks (0.027) and gold (0.006). In Panel C of Table 1 we report the average changes in the total share and the active shares of crypto currency trades, stock trades and gold. The size of the changes in the portfolio are not too different between the different assets. The changes in the active shares are typically a bit larger than the total shares, with the exception of cryptocurrency trades where the average of the total change and the passive change are quite similar. This results already foreshadows one of our main findings that investors are willing to hold crypto investments and not re-balance their portfolio when the price

[5] https://investors.robinhood.com/news/news-details/2022/Robinhood-Reports-Fourth-Quarter-and-Full-Year-2021-Results/

changes.

Given that these traders are drawn from around the world, a natural concern is that they may not represent the typical retail investor. Detailed data on retail traders' behavior are, in general, not publicly available and therefore directly measuring the representativeness of this data is difficult. To address this question using publicly available data we look compare the trading behavior of eToro investors to that of US retail investors. In short, we find that the two are highly correlated in the time series and cross section.

Specifically, we obtain the "Retail Trading Activity Tracker" from NASDAQ, which covers roughly 45% of US retail order flow. The data provides day-stock measures of "activity", the ratio of dollar traded by retail investors in a given ticker divided by total dollar traded by retail investors across all tickers, and "sentiment", measuring the retail net flows (buy minus sell) of the most recent 10 trading days. We aggregate individual trading behavior of eToro investors to produce parallel stock-day measures.

Next, we run panel regressions with either date, stock, or date and stock fixed effects for each of these measures with double-clustered standard errors. The results, reported in Table 2, are consistent and robust. The relation between US retail investors and that of eToro investors, as measured by these non-directional and directional measures is highly significant, with R^2s for activity being 65% and for sentiment being 10%.

3.1 Variable Design

We follow Calvet et al. (2009) and focus on share holdings out of portfolio value as the main dependent variable across a large number of specifications. Given that holding shares is highly persistent, we focus on changes and how they respond to asset returns. Specifically, we define Overall Share Change to be equal to $\frac{SharesOwned_t \times P_t}{Wealth_t} - \frac{SharesOwned_{t-1} \times P_{t-1}}{Wealth_{t-1}}$, where $SharesOwned_t$ is the number of shares owned at the end of day t, P_t is the unit price of the asset at the end of day t, and $Wealth_t$ is the portfolio value at the end of day t. Of course, there is a mechanical relationship between the return on the asset on day t and the the overall share change at the end of that day – even if the investor does not trade between time $t-1$ and time t, their returns and overall share change will be positively correlated since, other things equal, the asset will make up a larger part of the portfolio. To account for that, we also define Active Share Change as $(SharesOwned_t - SharesOwned_{t-1}) \times \frac{Price_{t-1}}{Wealth_{t-1}}$. This measure isolates the effect of trading, i.e., change in the number of shares between time $t-1$ and t, and does not incorporate any price t data.

To smooth out the noise in trading behavior of individual investors, we construct portfolios of various subsets of users and measure changes to these aggregate portfolios on the daily level for each stock and

crypto currency. Two baseline aggregations are: (1) treat all users on eToro, that are included in our sample, as one representative agent, and (2) include the subset of investors that, at some point, traded both the stocks and crypto currencies. Table 1 reports summary statistics for these two aggregate portfolio share changes.

4. Results

We now analyze the trading behavior of our retail investors as a function of past returns, comparing cryptocurrency trading to stocks and gold. Starting with the aggregate portfolio that includes all traders and stocks, we see that there is a strong dichotomy in trading between cryptocurrencies and both stocks and gold. The regression analysis follows this structure:

$$\begin{aligned} ShareChange_{t,i} = \alpha_i + \beta_1 LogReturn_{t,i} + \beta_2 LogCRet1Week_{t,i} + \beta_3 LogCRet1Month_{t,i} \\ + \beta_4 LogCRet3Month_{t,i} + \beta_5 LogCRet6Month_{t,i} + \epsilon_{i,t} \end{aligned} \tag{17}$$

Where $i \in Stocks$ or $i \in Cryptos$, with standard errors clustered by date. We include lagged cumulative 1 week, 1 month, 3 month, and 6 month returns as controls. For each cohort and asset class, we run separate regressions with overall share changes and with active share changes. Our focus of analysis is a comparison between stocks and crypto currencies responses' to returns. We also run separate regressions to observe any asymmetry in share change to negative relative to positive returns.

Table 3, presents the analysis for the full set of traders in our dataset, where we form cohort level aggregates at the individual asset level, as described in the data section. Thus, the unit of analysis in these regressions is day-asset. We regress changes in the log of the change in the total portfolio share of a security on the returns of that security on the same day, as well as log cumulative returns for the past 1 week, 1 month, 3 months and 6 months. These are calculated as overlapping returns to mimic time periods that might be salient to investors. In Panel A, we report the results for cryptos, in Panel B for stocks, and in Panel C for gold.

In Panel A, we examine how trading in cryptos responds to contemporaneous and past returns. We focus on the top three traded cryptos: Bitcoin (BTC), Etherium (ETH), and Ripple (XRP). We see that the change in the total share for cryptocurrencies is strongly, positively related to same day returns and more weakly related to the last week log cummulative returns. Beyond a week there is no economically meaningful relationship with further out returns and the estimated coefficients are close

to zero.[6] In columns (2) and (3) we then breakout the returns into days with positive versus negative contemporaneous returns, respectively. We see that the sign and magnitude of the estimated coefficient on same day returns are very similar for days with positive versus negative returns. One small difference is that for days with positive returns the one week lagged returns also have a positive and borderline significant relationship, but the magnitude of the effect is smaller. In contrast, for days with negative returns the total share change only the contemporaneous returns are significant. Overall these results suggest that for cryptocurrencies retail investors are willing to increase their share in cryptocurrencies after a price increase. In columns (4) through (6) we then repeat the same regression specifications but use as the dependent variable the log of the change in the active share. The active share captures the re-balancing investors do after taking into account the passive price changes. The coefficient on the log same day return is insignificant and close to zero in all specifications. But the coefficient on the lagged one week cumulative returns is positive and significant at the 5% level. These results suggest that investors are not actively re-balancing out of crypto in response to positive price changes and, if anything, are moving more money into cryptocurrencies as the prices increase with a one week lag.

In Panel B of Table 3, when looking at the same type of analysis for stocks we find a stark difference between how investors respond to stock returns relative to crypto returns. In this analysis we focus on the 200 most traded stocks on eToro to ensue that we have enough trading activity on a day-to-day basis.[7] In columns (1), as with cryptos, we first include all days, with positive and negative returns. The coefficients on the contemporaneous log returns and the one week lagged cumulative returns are negative, which means that retail traders actively reduce exposure to stocks whose price appreciates and increase exposure to stocks whose price depreciates. When we break out the results into positive and negative return dates, we find a stronger negative response on positive return dates than on negative return dates. This difference in the responses is consistent with the disposition effect, though the difference in the coefficients is only marginally significant. However, when repeating the same analysis with log of the change in the active share as the dependent variable, the coefficients in response to contemporaneous returns, in columns (4) to (6), are negative and economically large and significant. There is a much weaker, but still borderline significant, negative relationship for one week lagged returns. These results are in line with the changes in the total share change in columns (1) - (3). Retail investors are actively re-balancing out of stocks when prices go up, and put money into stocks when the prices go down. Broadly speaking, investors appear to be contrarians when trading stocks but not when trading crypto

[6] We also ran these regressions using separate dummies for returns one day out, two days out and so on for the whole week. But the results are not materially changed.

[7] For the list of the top 200 stocks by eToro trading, refer to Table A1. We also repeated the analysis for many different subsets of the data, e.g. the top 50 or all stocks and the results are qualitatively not changed.

currencies.

In Panel C of Table 3 we then repeat the same analysis for investments in gold. Here again we see very strong contrarian trading, with the coefficient of total share changes on log contemporaneous returns having almost the same size as the coefficient for active changes. This finding suggests that retail investors very actively reduce their position in response to price changes. Interestingly, the results show that investors seem to believe that gold and stock prices have a more similar return dynamics, while crypto currencies indeed truly are different. So at least when it comes to how retail investors trade, crypto does not seem to be the new gold.

Extreme Realizations of Returns. To further describe the nature of trading strategies across stocks and cryptocurrencies, we now test whether the effects are driven by days with extreme price movements. For this analysis, we repeat our main specification but divide the sample into quintiles based on their contemporaneous day returns. Panel A of Table 4 reports the results on the total share and Panel B on active share.

The difference in the distribution of returns for stocks, gold, and crypto currencies is quite large, with the later, on average, more volatile and more skewed, see Panel B of Table 1. In our sample period, the 20% (80%) percentile of daily returns for stocks was -1.25% (1.39%), for gold was -0.41% (-0.38%), while for crypto currencies it was roughly double the ones for stocks – -2.60% (2.89%). Table 4 shows that the change in total shares and active shares for cryptocurrencies, stocks, and gold. In Panel A, for cryptocurrencies we see that the total share moves particularly strongly when returns are in the bottom and the top quintiles, i.e. quintile 1 for the worst performance days and quintile 5 for the best performance days. The relationship is weaker for the middle quintile and even turn positive for quintile 3. But when looking at the active share in crypto trading, in Pane B, we see that throughout all quintiles we do not see any differential re-balancing in response to past returns. In other words, crypto investors do not seem to re-balance even around days with extreme positive or negative return realizations.

When looking at the stock and gold return quintiles, the picture is quite different. Investors are much more contrarian especially extreme positive or negative returns. When looking at active re-balancing in Panel B, we see a very strong contrarian trading response in the top and bottom quintiles, while the estimated effect is much weaker and in the middle quintile even positive (but not significant). In sum, this suggests that the contrarian trading in stocks and gold is particularly concentrated on days when there are large price movements, either positive or negative. The effect is much smaller interim-return days. In contrast, for cryptocurrencies, we see no change in active re-balancing, independent of the return quintile. In other words, investors do not re-balance even after very large price movements. The change in total share is very large especially in the top and bottom quintiles. But this has to be

mechanically true, since investors do not undo the changes in the portfolio through active trading.

4.1 Asset or trader driven?

A natural question when interpreting the above differences in trading behavior for stocks and cryptocurrencies is whether these results are due to self-selection of investors with different preferences into different asset classes, or due to different belief-formation models across these assets. After all, investors are not randomly assigned to trading stocks or crypto currencies. However, one strength of our data is that it allows us to observe how *the same individuals* trade across the two types of assets. The analysis in Table 5 shows the results for two groups of users: those who, at some point, traded both stocks and crypto currencies, versus those who exclusively either traded stocks or cryptocurrencies. Across the two subgroups we find a qualitatively similar trading pattern as in the overall sample.

In Panel A of Table 5 we report the results for the set of investors who traded in both crypto and stock. About 64% of traders in our sample are in this category. The regression set up is exactly the same as in Table 3 but we form a cohort based on the above users only and we only report the coefficient on the log contemporaneous returns, since the lagged returns are not significant. As in the sample with all traders, we see the stark dichotomy: investors are contrarian in stock trading but momentum in crypto when looking at the changes in total portfolio shares. The size of the coefficients is quite similar to the full sample as well. And similarly to Table 3, the analysis of the active share shows that our investors actively re-balance out of stocks after periods of positive returns, but do not adjust their crypto positions in response to price changes.

In Panel B of Table 5 we then break out the investors who exclusively trade either in crypto or stocks. Here we again see in Columns (1) through (3) that traders who exclusively trade in crypto are momentum traders, i.e. their total share changes positively with log returns. And when looking at the active share, we see that they do not re-balance in response to price changes. In Columns (4) to (6) we finally look at people who only trade in stocks. Here we find a slightly muted dynamic. When looking at the changes in the active share in Panel B, we see that these investors re-balance and take money out of stocks after positive returns, which also leads to a change in the total share in these periods. But on days when the returns are negative they seem to not re-balance and thus their total share goes down as well.

In sum, these results suggest that the difference in trading behavior is *not* a result of different types of retail investors engaging in cryptocurrencies versus another investing in stocks. Instead even when focusing on the same investors, they seem to update their future return beliefs differently for crypto currencies relative to stocks.

4.2 Investor Heterogeneity

While we have shown that the dichotomy in trading behavior of stocks and crypto is a *within-person* phenomenon, we now want to further understand if some subgroups of the population are driving this effect. It is possible that there are a few large trades of crypto-currencies that display this very dichotomous behavior across the different assets. For this purpose, we dive into the effect of individual characteristics on trading behavior. We separate traders based on the set of personal characteristics that can be identified on the platform. The dimensions we focus on are gender ('Female' identifies the set of women on the platform), experience ('New Trader' dummy = 1 for traders with less than 1 year of trading experience when joining eToro), finance experience ('Finance Profession' dummy = 1 for traders who indicated that they worked in the finance industry), wealth ('Low wealth' = 1 for traders indicating total cash or liquid assets of less than $10,000), age ('Young' dummy = 1 for users younger than 35), and their crypto affinity ('First crypto' = 1 for traders who traded crypto currencies before trading in any other asset class). Table 6 reports the results splitting the analysis by cohorts formed on the basis of each of these characteristic dummies, one at a time. For example, when analyzing heterogeneity across gender we form male and female cohorts across all the different assets. We then repeat the analysis of Table 3 but add an interaction term of the log same day returns with the characteristic in question.

Overall the analysis of personal characteristics shows that all groups are quite similar in their trading behavior. The coefficient on log returns is consistently negative and significant for stock trades and positive and significant for crypto trades. In other words, the dichotomy between being momentum in crypto and contrarian in stocks is robustly present across traders and it is not driven by a specific subset.

We do find that some groups are a bit less muted in their responses. For example, when looking at cryptocurrencies, we find that investors with lower wealth react slight less to log returns and are thus slightly less momentum then more affluent investors. This holds for the change in total share and active share. But the results are only borderline significant. So in sum, it seems that there is quite a lot of similarity in how different investors trade in crypto-currencies versus other investments.

4.3 Investor (In)Attention

One potential concern in interpreting our results on crypto trading, especially the fact that investors in crypto-currencies do not significantly re-balance when the price of the coins change, could be due to inattention or inertia. As discussed before, if investors allow the total share in cryptocurrencies to move up and down with prices, while not paying attention to these investments, total changes in portfolio shares would not be an indication of how investors update about the prices of these securities.

To address this concern we first note that the same investors during the same time period actively traded out of stocks when their prices go up and vice versa when prices increase. Thus, inattention would have to only apply to crypto-currencies and not to stocks. This would seem quite unlikely in our context since once an investor logs into their eToro account they can immediately see both types of investments. But to test this channel more directly, we now repeat the analysis from Table 3 but form investor cohorts based on their activeness: active users are defined as users who traded at least once during the previous calendar month (in any asset) while inactive investors are defined traded less actively.

Table 7 reports the results. We find that for the group of active investors the result are parallel to our overall results: the total share change is positive for crypto currencies and strongly negative for equities. When looking at the active share for these attentive investors, we see that they are not re-balancing their crypto holding actively in response to return changes but are very active in their stock investments. However, when we look at the inactive investors we see an interesting difference: Focusing on the total share in Panel A, we see that their total portfolio shares in both cryptocurrencies and stocks moves positively with log returns, in other words, they are momentum in both stocks and cryptocurrencies. When looking at the active share changes for these investors we see the explanation for this change – the change in the active share as a function of past returns is only a third of the coefficient for the attentive investors. This suggests that our metric of inattention seems to be doing a good job in filtering out investors who do not pay attention to their portfolio and therefore ride up and down passively with price changes. Most importantly the results suggest that for the attentive investors we find that they are still displaying a strong dichotomy in crypto versus stock investments, mirroring our main specification results.

4.4 Robustness Checks

Compositional Changes One might worry that compositional changes could affect our cohort construction, since especially early in the sample period new investors are entering eToro and also starting to adopt cryptotrading and other assets. In order to control for such early adoption concerns, we repeat our results in Table 8 but only include retail investors who have been active on the platform for at least 90 days. The rest of the specification is identical Table 3. Panel A reports the changes in total share, for cryptocurrencies and stocks. And Panel B reports the changes in the active share. We see that the results are virtually unchanged from Table 2 when we use the full sample. This confirms that our results are not driven by some unintended dynamics where traders who enter the platform distort the observed trading patterns, since these investors are establishing a new portfolio.

Individual Transactions We also want to confirm that our results are not driven by using the cohort level aggregation. Therefore, in Table 9 we repeat our analysis at the individual level. We keep investors who traded in both cryptos and stocks during their tenure at eToro, and include investor fixed effects. We examine the top 50% of investors in our sample, by the number of days they traded either crytos or stocks. We end up with 58,954 users. We rerun our main specification, but we include instrument, date, and individual investor fixed effects. We find similar results to our main specification. This suggests that our results are not distorted by aggregation into cohorts.

5. Why is crypto different?

We now try to shed some light on why investors differ in how they form price expectations for crypto currencies compared to stocks. Cryptocurrencies are an entirely new investment vehicle, whose future value to a large extent depends on investors' beliefs about whether there will be wider market adoption going forward, see also Biais et al. (2020) or Kogan et al (2022) for a formalization of this idea. Since there are few fundamentals that predict the path or speed of adoption, investors might use the price movements as an indicator of future adoption. In other words, when the price of cryptocurrencies goes up for any reason, it might also lead to an amplification effect in the price, since investors believe that a higher price makes it more likely that other investors, or even regulators, look more favorably at cryptocurrencies going forward. This type of belief structure could explain the momentum trading behavior displayed among our retail investors. This same amplification effect is not present in stocks or even gold.

But there are also a number of alternative channels that could affect our results. The specific candidate explanations we investigate are whether prior to 2018 investors had never experienced a crash in cryptocurrencies and thus were willing to hold on to them through smaller price movements. Second whether investors are willing to invest in lottery like assets differently than other types of securities, in other words would any stock that has similarly skewed results as cryptocurrencies had over the the last years, see similar momentum investment strategies. And finally, we analyze whether the lack of cash flow information explains the difference between cryptocurrencies and stocks.

Cryptocurrency crash. Prior to 2018 cryptocurrencies like Bitcoin or Ethereum had seen very large run ups in prices and a lot of volatility but had not experienced any significant crash in crypto. However, the beginning of 2018 was the first major crash in BTC and other coins. The price of bitcoin fell by about 65% from the beginning of January to February 2018. To analyze if the experience of the crash significantly changed trading behavior of retail investors, in Table 10 we now repeat our cohort analysis

from Table 5, using only investors who are active in both stocks and cryptocurrencies, and who traded in the seven days prior to ensure that these are investors who actively engage with their portfolios. In addition, we now include an interaction term of log contemporaneous returns with a dummy for the pre-2018 period and the period post February 2018. Panel A records the changes in the total portfolio shares and confirms as previously found that for cryptocurrencies, investors follow a momentum strategy pre-2018, i.e. the coefficient on log returns is positive and very significant. Post-2018, this momentum strategy is slightly muted for cryptocurrencies, since the coefficient on log returns $\times$ the after crash dummy is negative and significant. When adding the coefficient on the interaction term to the direct effect, the overall effect is reduced by about 15%. But overall, investors are still following a momentum strategy even after 2018. [8] This interpretation is confirmed in Panel B of Table 10 where we look at the active share before and after the 2018-crash. Again we see that investors are re-balancing more actively after the 2018 crash in cryptocurrency prices, but the overall effect does not undo the momentum strategy. In comparison, trading in stocks does not show any changes before and after 2018, which should not be surprising since the crash was localized in cryptocurrencies and stock markets did not react significantly to it.

In Appendix Table A2 we also analyze if certain subgroups of traders were more likely to change their momentum strategy in crypto-trading after the experience of the crash. For this purpose we interact the post crash x log return term with the same individual characteristics as before. However, we do not find that there are any subgroups of traders that show significantly larger sensitivity to the crash. The one significant exception are for Guru traders. For this group we in fact see that they became even more momentum traders after 2018. However, it is difficult to know if this is a reflection of their own preferences, or if this trading strategy is aimed at drawing in retail investors to follow them. In sum, we find that the 2018 crash in crypto-prices did not materially change the trading behavior of retail investors. While there is slightly more re-balancing after price changes post-2018, over all retail investors stayed strongly momentum traders in cryptocurrencies.

Skewness of Returns. An alternative explanation for retail investor trading of cryptocurrencies might be that investors are holding on to assets that have very skewed or volatile returns since they treat them like lottery tickets. Several studies have documented that retail investors have a preference for skewness in returns and will hold lottery-like stocks. Kumar (2009) and Mitton and Vorkink (2007) propose that retail investors have a taste for stocks with lottery-like payoffs. Dorn et al. (2015) or Gao and Lin (2011) show that trading by individual investors declines during periods with unusually large lottery jackpots, especially in stocks with high levels of individual investors participation and skewed returns.

[8] These results hold also when we focus on the full set of investors, not only those who traded in the last seven days.

In other words, what is special about cryptocurrency is just the nature of the observed returns. But in that case, any other asset with similarly skewed returns would be treated the same way. To test the validity of this hypothesis, we utilize the cross-section of stock returns and ask whether stocks that are often seen as more lottery-like, for example those that have higher volatility, skewness, or are younger induce also more "crypto-like" behavior. We again focus on the sample of the top 200 stocks on eToro and only look at investors who have traded both cryptos and stocks during their tenure at eToro. The stock characteristics we measure are return volatility, which is defined as the standard deviation of daily returns over the past calendar month. Return skewness is measured as the skewness of daily returns over the past calendar month. The maximum daily stock return is, again, measured over the past month. And a dummy for young firm, which is defined as firm that are less than a year old. Finally, gross profitability is defined as revenues minus cost of goods sold divided by lagged total assets.

Table 11 reports the results, where we interact each of these characteristics, one at a time, with the log return of the stock. The results are somewhat mixed and not strongly consistent with the idea that users who trade lottery like stocks exhibit more momentum behavior. When looking at the maximum past returns as the dimension of heterogeneity, we find that the change in total share as a function of log returns is less negative (and borderline significant) for share that had high last month maximum returns. However this relationship is only positive for days with positive returns and negative for days with negative returns. However, when using return volatility or return skewness as the measure of heterogeneity, we find, if anything, that investors are more contrarian on these stocks. When regressing change in total share on the interaction between these characteristic and log returns the estimated coefficient is negative and significant in both cases. Finally, we don not find significant difference for stocks based on their age and profitability. In total, we do not find evidence to suggest that investors treat all assets with very skewed or volatile returns symmetrically and engage in momentum trading for these assets. It rather seems that this momentum strategy is unique to cryptocurrencies.

Lack of cash flow information. Finally, a difference between cryptocurrencies and stocks is that the former lack anchoring in regularly observable fundamentals such as firm earnings or free cash flows. The lack of information events about fundamentals such as earnings announcements for stocks, might affect how investors update their beliefs about prices. For example, Luo et al. (2020) suggests that momentum returns are largely driven by retail contrarian trading in response to earnings announcements. Cash flow news might trigger a reevaluation of investor beliefs about whether the stock price is too high or too low, because of other investors excessive optimism or pessimism. Thus, the contrarian trading after earnings announcements follows from their desire to take advantage of their perception that markets overreact to news. This same dynamic might not be at play in cryptocurrency prices which lack regular cash flow

news.

In Table 12 we therefore follow Luo et al. (2020) and analyze whether the contrarian trading that we observe in stocks is focused predominantly around earnings announcements. For this purpose we separate our data into two subsamples: days that have earnings announcements, in columns (1) to (3), compared to those that are non-earnings announcement dates, in columns (4) through (6). We again look at change in the total portfolio shares in Panel A and the active share in Panel B. The first three columns show that on days where a stock had an earnings announcement the coefficient on log returns is twice as large as for the sample over all, whether we look at the total share change in Panel A or the active share in Panel B. The results for the non earnings announcement dates, are weaker when we look at the total share change. The coefficients on log returns are negative but not significant at conventional levels. When looking at the active share change, we find contrarian re-balancing that is almost as large as in the fully sample: The coefficient on log returns is negative and significant. Overall, these results suggest that while contrarian re-balancing in stocks is particularly strong around earnings announcement dates, the effect is persistent throughout the sample.

6. Conclusion

Using trade level data of retail investors on eToro, a leading discount brokerage platform, we find that investors seem to use a different model when updating their price expectations for cryptocurrencies compared to other assets. The same set of investors who adopt a contrarian strategy when investing in stocks or gold, show a momentum strategy when investing in crypto currencies. The comparison to gold is interesting, since it is often touted as the model for crypto investments. We also show that the momentum trading in cryptocurrencies is mainly driven by the fact that retail investors are willing to hold on to their cryptocurrency investments even in the face of large price swings. They are not actively rebalancing out of them when prices rise sharply ("profit taking") nor do they double up when the prices drop. We confirm that this dichotomy in trading behavior is not driven by composition effects of who trades crypto, nor inattention to crypto prices so that people are passively affected by price swings without understanding it. We also show that the results are not a naïve version of optimism where investors had never seen crypto prices crashing before and believe that they can only go up. In a nutshell, cryptocurrencies indeed seem to be special in retail traders' minds. Interestingly, this dichotomy in trading behaviors holds for a majority of retail investor types and heterogeneity in individual characteristics explains only a very small fraction of how people invest in cryptocurrencies. In other words, independent of age, financial education, income and several other characteristics, we see

the same momentum trading in cryptocurrencies.

Our results point to a model where investors seem to form adaptive expectations about cryptocurrency prices. What is behind this type of beliefs? On the one hand, retail investors might be prone to positive and negative sentiment cycles, or they might have convinced themselves that crypto currencies are the newest investment vehicle and thus they need to invest in them no matter what the price dynamic is. But on the other hand, there might also be a less sentiment driven explanation. The value of cryptocurrencies is largely based on expectations about potentially wider future adoption, which in turn might be influenced by their current value. Positive returns of cryptocurrencies might increase the likelihood that regulators look more favorably at them, or that institutional investors start investing in them. This would create positive (and negative) feedback loops and could naturally justify the momentum strategies we see in our data. This same price dynamic is not observed for other assets where adoption has already happened and most people who ultimately want to invest in the asset are already participating. This explanation would also be in line with a few earlier studies using aggregate price data which have shown that cryptocurrency prices react to news about cryptocurrency adoption, see for example Auer and Claessens (2018) or Biais et al. (2020). While price information is available at much higher frequency than news announcements, say about regulatory changes, in the absence of cash flow news investors might rely on price movements to update their expectations. Of course, a lot more work is needed to analyze how investment behaviors change once participants have a longer time series of prices to learn from, or adoption is approaching a point of saturation. Similarly, it would be useful to understand what drives heterogeneity across investors or how the introduction of many new cryptocurrencies affects trading behaviors.

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7. Tables and Figures

Figure 1. **Amount Invested over Time**

In this figure we plot the dollar amount invested in each asset class over time at the monthly level.

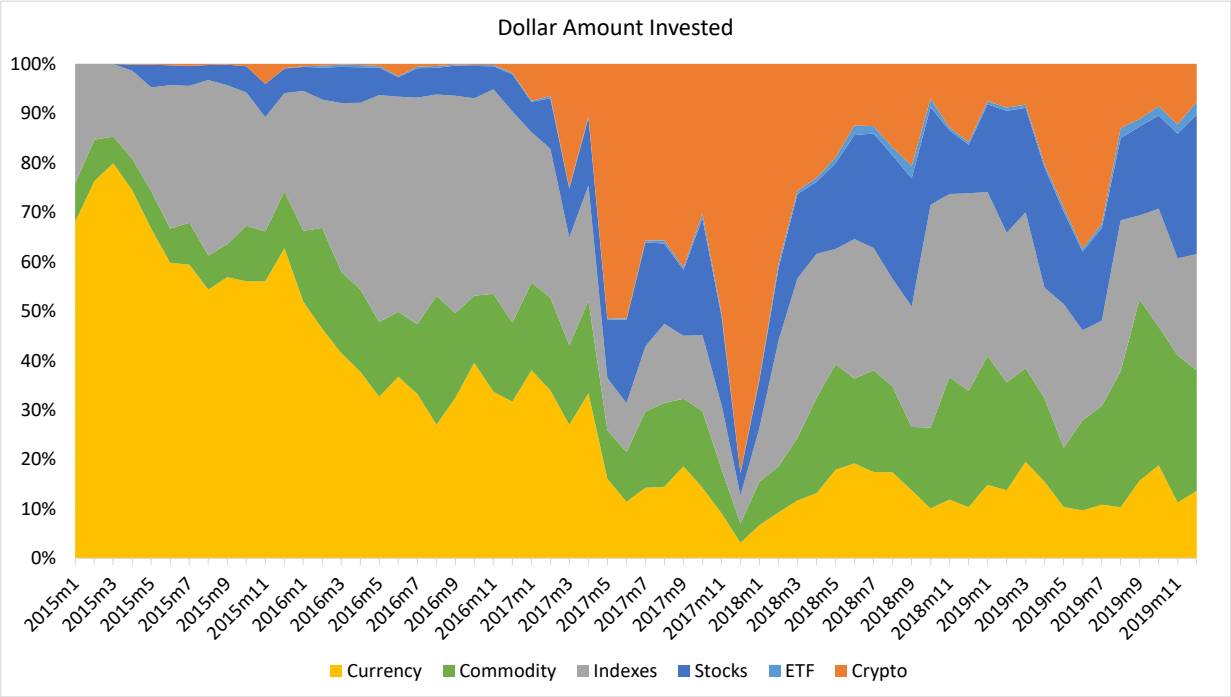


Table 1. **Summary Statistics**

This table displays the summary statistics for our main variables. In Panel A, we display trader characteristics. In Panel B, we show the distribution of log returns for the three asset classes that we examine in this paper. $Log(Ret)$ is defined as log of return on day t. Panel C shows the distribution of log(total share change) and log(active share change) for the three asset classes. $Log(\text{Total Share Change}_t)$ defined as $\log(\text{Active Share Change}_t) + \log(Price_t/Price_{t-1}) - Log(Wealth_t/Wealth_{t-1})$. $Log(\text{Active Share Change}_t)$ is defined as $\log(\text{Shares owned}_t) - \log(\text{Shares owned}_{t-1})$.

Panel A

	Mean	SD	Min	p25	p50	p75	p90	Max	Obs
Num trades per user	79.51	249.31	1	6	20	66	183	25,888	206,074
Num unique instruments	14.01	27.27	1	2	5	14	34	901	206,074
Num unique stocks	12.15	27.06	0	0	3	12	32	898	206,074
Num unique cryptos	1.86	1.08	0	1	2	3	3	3	206,074
Account age	448.94	424.99	0	61	318	814	1,009	1,947	201,760
New traders	0.50	0.50	0	0	1	1	1	1	206,074
Financial Industry	0.20	0.40	0	0	0	0	1	1	206,074
Low Wealth	0.43	0.49	0	0	0	1	1	1	206,074
Young	0.51	0.50	0	0	1	1	1	1	206,074
Guru	0.01	0.10	0	0	0	0	0	1	206,074
Holding Period Crypto	53.06	112.43	0	3	12	48	141	1,162	172,792
Holding Period Stock	21.14	49.71	0	2	7	20	49	1,904	150,907

Panel B

	Mean	SD	Min	p25	p50	p75	p90	Max	Obs
Log(Ret Stocks)	0.00001	0.0270	-1.499	-0.0097	0.0006	0.0108	0.0239	0.873	172,444
Log(Ret Crypto)	0.00161	0.0526	-0.348	-0.0180	0.0010	0.0209	0.0522	0.583	3,586
Log(Ret Gold)	-0.00002	0.0060	-0.031	-0.0032	0.0000	0.0030	0.0067	0.040	1,308

Panel C

	Mean	SD	Min	p25	p50	p75	p90	Max	Obs
All Investors: Crypto									
Log(total share change)	0.0039	0.0628	-0.5429	-0.0169	-0.0008	0.0187	0.0522	0.9032	3,586
Log(active share change)	0.0041	0.0479	-0.5483	-0.0031	0.0004	0.0061	0.0247	0.9042	3,586
All Investors: 200 Stocks									
Log(total share change)	0.0031	0.3655	-17.6411	-0.0405	0.0002	0.0421	0.1285	17.2385	172,444
Log(active share change)	0.0059	0.3658	-17.5605	-0.0291	0.0000	0.0353	0.1265	17.2176	172,444
All Investors: Gold									
Log(total share change)	0.0032	0.5302	-6.4706	-0.0980	0.0046	0.1022	0.2909	6.1139	1,308
Log(active share change)	0.0051	0.5315	-6.4755	-0.0905	0.0061	0.1048	0.2929	6.1356	1,308

Table 2. **NASDAQ vs eToro Equity Trading**

This table presents panel regressions of Activity (unsigned retail order flow) and Sentiment (net signed order flow) as reported by NASDAQ 'Retail Trading Activity Tracker" on the same measure computed for eToro. These measures are calculated for each stock/date in our sample. In columns 1-3, the variable of interest is Activity and in columns 4-6 the variable of interest is Sentiment. Each of the columns uses a different set of controls: Firm fixed effects, Date fixed effects, and Firm and Date fixed effects. In all cases standard errors are clustered by firm and date. Statistical significance is denoted at the ten, five, and one percent levels by *, **, and ***, respectively.

	Firm FE (1)	Date FE (2)	Firm and Date FE (3)	Firm FE (4)	Date FE (5)	Firm and Date FE (6)
Activity	0.077***	0.158***	0.077***			
	(8.49)	(11.67)	(8.50)			
Sentiment				0.008***	0.008***	0.007***
				(13.19)	(12.19)	(12.17)
Observations	1,125,736	1,125,736	1,125,736	697,016	697,016	697,016
R-squared	0.65	0.35	0.65	0.07	0.03	0.10

Table 3. **Overall and Active Share Change: Cryptos vs. Stocks**

In this table we examine how contemporaneous and lagged returns affect individuals' trading behavior. We generate a representative investor, by cumulating trades, net inflows, and wealth, across all investors who participated on the platform at date t. Log(Total Share Change$_t$) is defined as log(Active Share Change$_t$) + log($Price_t/Price_{t-1}$) − $Log(Wealth_t/Wealth_{t-1})$. Log(Active Share Change$_t$) defined as log(Shares owned$_t$) − log(Shares owned$_{t-1}$). $Log(Ret)$ is defined as log of return on day t, and Log(CR past 1 week) is defined as the cumulative return over the past 7 days. In Panel B Log(Wealth Ret$_t$) is defined as log($[Wealth_t - NetInflows_t]/Wealth_{t-1}$), and log(Ret Net Inflows) is defined as log($Wealth_t/Wealth_{t-1}$) − log($(Wealth_t - NetInflows_t)/Wealth_{t-1}$). Log returns are standardized within asset class across the entire time period, and denoted with (z). In Panel A, we examine cryptos, in Panel B stocks, and in Panel C gold. *Cryptos* are BTC, XRP, and ETH. For the list of the top 200 stocks by eToro trading, refer to Table A1. Standard errors are clustered at the date level and reported in parentheses. Statistical significance is denoted at the ten, five, and one percent levels by *, **, and ***, respectively.

Panel A: Crypto

	Log(total share change)			Log(active share change)		
	All	Ret>0	Ret≤0	All	Ret>0	Ret≤0
	(1)	(2)	(3)	(4)	(5)	(6)
Log(Ret) (z)	0.035***	0.039***	0.031***	-0.001	0.002	-0.006***
	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Log(CR past 1 week) (z)	0.002**	0.005**	-0.000	0.003**	0.004**	0.001
	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)
Log(CR past 1 month) (z)	0.001	0.002	-0.001	0.000	0.001	0.000
	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Log(CR past 3 months) (z)	-0.004**	-0.003	-0.006**	-0.005***	-0.003*	-0.007**
	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)
Log(CR past 6 months) (z)	0.005**	0.002	0.007**	0.004**	0.000	0.008**
	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)
Log(Ret Wealth) (z)				0.001	-0.000	0.004**
				(0.001)	(0.002)	(0.002)
Log(Ret Net Inflows) (z)				0.006***	0.006***	0.004**
				(0.001)	(0.002)	(0.002)
Outcome SD	0.063	0.063	0.056	0.048	0.049	0.047
R2	0.325	0.378	0.271	0.023	0.032	0.035
Observations	3,586	1,866	1,720	3,586	1,866	1,720

Panel B: Stocks

	Log(total share change)			Log(active share change)		
	All	Ret>0	Ret≤0	All	Ret>0	Ret≤0
	(1)	(2)	(3)	(4)	(5)	(6)
Log(Ret) (z)	-0.006***	-0.006**	-0.006**	-0.026***	-0.024***	-0.028***
	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)
Log(CR past 1 week) (z)	-0.003**	-0.005**	-0.001	-0.003**	-0.005***	-0.001
	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)
Log(CR past 1 month) (z)	-0.002	-0.003*	-0.001	-0.002*	-0.004**	-0.001
	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)
Log(CR past 3 months) (z)	0.002	0.004	-0.001	0.002	0.004	-0.001
	(0.002)	(0.004)	(0.002)	(0.002)	(0.004)	(0.002)
Log(CR past 6 months) (z)	0.001	-0.000	0.002	0.002	0.001	0.003
	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)
Log(Ret Wealth) (z)				0.006***	0.004**	0.007**
				(0.002)	(0.002)	(0.003)
Log(Ret Net Inflows) (z)				-0.000	0.000	-0.001
				(0.001)	(0.001)	(0.002)
Outcome SD	0.363	0.370	0.355	0.363	0.370	0.355
R2	0.001	0.001	0.001	0.008	0.006	0.011
Observations	170,878	87,894	82,984	170,878	87,894	82,984

Panel C: Gold

	Log(total share change)			Log(active share change)		
	All	Ret>0	Ret≤0	All	Ret>0	Ret≤0
	(1)	(2)	(3)	(4)	(5)	(6)
Log(Ret) (z)	-0.216***	-0.213***	-0.205***	-0.221***	-0.215***	-0.215***
	(0.027)	(0.035)	(0.034)	(0.027)	(0.034)	(0.035)
Log(CR past 1 week) (z)	0.029*	0.020	0.037*	0.029*	0.023	0.034
	(0.016)	(0.023)	(0.021)	(0.016)	(0.023)	(0.021)
Log(CR past 1 month) (z)	0.012	0.012	-0.005	0.013	0.007	-0.001
	(0.031)	(0.050)	(0.034)	(0.031)	(0.049)	(0.035)
Log(CR past 3 months) (z)	-0.004	-0.063**	0.064**	-0.005	-0.064**	0.060**
	(0.022)	(0.031)	(0.030)	(0.022)	(0.031)	(0.030)
Log(CR past 6 months) (z)	0.008	-0.015	0.030	0.007	-0.015	0.029
	(0.017)	(0.027)	(0.021)	(0.017)	(0.027)	(0.021)
Log(Ret Wealth) (z)				0.006	-0.008	0.018
				(0.014)	(0.018)	(0.020)
Log(Ret Net Inflows) (z)				-0.018	-0.013	-0.022
				(0.015)	(0.020)	(0.021)
Outcome SD	0.546	0.565	0.476	0.547	0.565	0.477
R2	0.158	0.149	0.215	0.165	0.155	0.227
Observations	1,146	585	561	1,146	585	561

Table 4. **Return Quintile Analysis**

In this table we examine whether investors respond to returns differently for different return quintiles. We generate a representative investor, by cumulating trades, net inflows, and wealth, across all investors who participated on the platform at date t. We only look at investors who have traded both cryptos and stocks during their tenure at eToro. $Log(\text{Total Share Change}_t)$ and $Log(\text{Active Share Change}_t)$ are defined as in Table 3. Controls include lagged 1 week, 1 moth, 3 month, and 6 month cumulative returns for total and active share change regressions, as well as returns on wealth and net inflows, for active share change. *Cryptos* are BTC, XRP, and ETH. For the list of the top 200 stocks by eToro trading, refer to Table A1. The cutoffs for cryptos are: -0.025, -0.005, 0.007, and 0.029; the cutoffs for stocks are: -0.013, -0.003, 0.004, and 0.014; the cutoffs for gold are: -0.0041, -0.0008, 0.001, and 0.00385. Log returns are standardized within asset class across the entire time period, and denoted with (z). Standard errors are clustered at the date level and reported in parentheses. Statistical significance is denoted at the ten, five, and one percent levels by *, **, and ***, respectively.

Panel A

	Log(Total Share Change)				
	Bottom Quintile	2	3	4	Top Quintile
			Cryptos		
Log(Ret) (z)	0.036***	0.014	-0.056	0.053***	0.039***
	(0.003)	(0.017)	(0.053)	(0.016)	(0.003)
Controls	Yes	Yes	Yes	Yes	Yes
Outcome SD	0.046	0.047	0.058	0.050	0.060
R2	0.239	0.035	0.004	0.029	0.296
Observations	718	717	717	717	717
			Top 200 Stocks		
Log(Ret) (z)	-0.028***	0.028*	0.063**	-0.015	-0.028***
	(0.007)	(0.015)	(0.024)	(0.019)	(0.007)
Controls	Yes	Yes	Yes	Yes	Yes
Outcome SD	0.437	0.334	0.357	0.329	0.443
R2	0.005	0.000	0.000	0.001	0.003
Observations	33,693	34,095	34,136	34,092	33,775
			Gold		
Log(Ret) (z)	-0.145**	-0.159	-0.222	-0.130	-0.109**
	(0.063)	(0.141)	(0.135)	(0.141)	(0.055)
Controls	Yes	Yes	Yes	Yes	Yes
Outcome SD	0.569	0.286	0.201	0.342	0.508
R2	0.086	0.059	0.032	0.006	0.133
Observations	225	222	238	236	228

Panel B

	Log(Active Share Change)				
	Bottom Quintile	2	3	4	Top Quintile
			Cryptos		
Log(Ret) (z)	-0.001	-0.005	-0.084	0.013	-0.002
	(0.003)	(0.012)	(0.054)	(0.015)	(0.004)
Controls	Yes	Yes	Yes	Yes	Yes
Outcome SD	0.046	0.047	0.058	0.050	0.060
R2	0.034	0.070	0.009	0.025	0.071
Observations	718	717	717	717	717
			Top 200 Stocks		
Log(Ret) (z)	-0.055***	0.011	0.038	-0.039**	-0.056***
	(0.007)	(0.015)	(0.024)	(0.019)	(0.007)
Controls	Yes	Yes	Yes	Yes	Yes
Outcome SD	0.437	0.334	0.357	0.329	0.443
R2	0.020	0.001	0.000	0.001	0.012
Observations	33,693	34,095	34,136	34,092	33,775
			Gold		
Log(Ret) (z)	-0.147**	-0.173	-0.213	-0.128	-0.111**
	(0.063)	(0.146)	(0.131)	(0.146)	(0.055)
Controls	Yes	Yes	Yes	Yes	Yes
Outcome SD	0.569	0.286	0.201	0.342	0.508
R2	0.107	0.060	0.038	0.007	0.139
Observations	225	222	238	236	228

Table 5. **By Investor Type**

In this table we examine whether investors who trade in both cryptos and stocks trade differently from investors who only trade in cryptos or only in stocks. We generate a representative investor, by cumulating trades, net inflows, and wealth, across all investors who participated on the platform at date t. An investor is defined as trading in cryptos (stocks) if she traded cryptos (stocks) at any time during her eToro tenure. $Log(\text{Total Share Change}_t)$ and $Log(\text{Active Share Change}_t)$ are defined as in Table 3. Controls include lagged 1 week, 1 moth, 3 month, and 6 month cumulative returns for total and active share change regressions, as well as returns on wealth and net inflows, for active share change. *Cryptos* are BTC, XRP, and ETH. For the list of the top 200 stocks by eToro trading, refer to Table A1. Log returns are standardized within asset class across the entire time period, and denoted with (z). Standard errors are clustered at the date level and reported in parentheses. Statistical significance is denoted at the ten, five, and one percent levels by *, **, and ***, respectively.

Panel A: Traded in both Cryptos and Stocks

	Log(total share change)					
	Cryptos			Top 200 Stocks		
	All	Ret>0	Ret≤0	All	Ret>0	Ret≤0
	(1)	(2)	(3)	(4)	(5)	(6)
Log(Ret) (z)	0.035***	0.040***	0.035***	-0.012***	-0.023***	-0.017***
	(0.001)	(0.002)	(0.002)	(0.002)	(0.004)	(0.005)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Outcome SD	0.066	0.065	0.061	0.383	0.388	0.378
R2	0.292	0.269	0.173	0.001	0.002	0.002
Observations	3,586	1,866	1,720	169,791	87,329	82,462

	Log(active share change)					
	Cryptos			Top 200 Stocks		
	All	Ret>0	Ret≤0	All	Ret>0	Ret≤0
	(1)	(2)	(3)	(4)	(5)	(6)
Log(Ret) (z)	-0.001	-0.000	0.000	-0.036***	-0.049***	-0.042***
	(0.002)	(0.003)	(0.003)	(0.002)	(0.004)	(0.005)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Outcome SD	0.052	0.052	0.053	0.383	0.388	0.378
R2	0.021	0.026	0.026	0.009	0.008	0.010
Observations	3,586	1,866	1,720	169,791	87,329	82,462

Panel B: Traded only Cryptos or Stocks

	Log(total share change)					
	Cryptos			Top 200 Stocks		
	All	Ret>0	Ret≤0	All	Ret>0	Ret≤0
	(1)	(2)	(3)	(4)	(5)	(6)
Log(Ret) (z)	0.031***	0.035***	0.028***	0.013***	-0.010*	0.031***
	(0.002)	(0.003)	(0.003)	(0.005)	(0.006)	(0.011)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Outcome SD	0.074	0.079	0.063	0.637	0.645	0.630
R2	0.181	0.154	0.112	0.001	0.001	0.002
Observations	3,583	1,866	1,717	151,725	77,995	73,730

	Log(active share change)					
	Cryptos			Top 200 Stocks		
	All	Ret>0	Ret≤0	All	Ret>0	Ret≤0
	(1)	(2)	(3)	(4)	(5)	(6)
Log(Ret) (z)	0.001	0.003	-0.004	-0.013**	-0.036***	0.005
	(0.003)	(0.004)	(0.003)	(0.005)	(0.006)	(0.011)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Outcome SD	0.062	0.067	0.056	0.637	0.645	0.629
R2	0.023	0.031	0.033	0.001	0.002	0.000
Observations	3,582	1,866	1,716	151,725	77,995	73,730

Table 6. **Investor Characteristics**

In this table we examine whether there is heterogeneity in how investors trade across investor characteristics. We generate two representative investors, by cumulating trades, net inflows, and wealth, across all investors who participated on the platform at date t, based on whether the investors have a certain characteristics or they don't. We only look at investors who have traded both cryptos and stocks during their tenure at eToro. We classify investors as having a *Finance Background* if she reported to work in the finance industry, as *Low Wealth* if she reports to have total cash/liquid assets *leq* \$10K, as *Young* if she is less than 35 years old when joining eToro, and as *Ever Guru* if she has been a guru at any point during her tenure at eToro. *Log*(Total Share Change$_t$) and *Log*(Active Share Change$_t$) are defined as in Table 3. Controls include lagged 1 week, 1 moth, 3 month, and 6 month cumulative returns for total and active share change regressions, as well as returns on wealth and net inflows, for active share change. *Cryptos* are BTC, XRP, and ETH. For the list of the top 200 stocks by eToro trading, refer to Table A1. Log returns are standardized within asset class across the entire time period, and denoted with (z). Standard errors are clustered at the date level and reported in parentheses. Statistical significance is denoted at the ten, five, and one percent levels by *, **, and ***, respectively.

Panel A

	Log(total share change)					
	Cryptos			Top 200 Stocks		
	All	Ret>0	Ret≤0	All	Ret>0	Ret≤0
	(1)	(2)	(3)	(4)	(5)	(6)
			Female			
Log(Ret) (z)	0.035***	0.040***	0.034***	-0.009***	-0.022***	-0.013***
	(0.001)	(0.003)	(0.002)	(0.002)	(0.004)	(0.005)
Investor Type	0.000	0.004	-0.004	-0.005	-0.011	-0.000
	(0.002)	(0.003)	(0.004)	(0.004)	(0.007)	(0.007)
Investor Type × Log(Ret) (z)	0.002	-0.000	-0.001	-0.016**	-0.011	-0.012
	(0.001)	(0.002)	(0.003)	(0.006)	(0.011)	(0.012)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Outcome SD	0.096	0.098	0.087	0.834	0.873	0.791
R2	0.148	0.118	0.084	0.001	0.001	0.001
Observations	7,167	3,732	3,435	303,049	155,969	147,080
			Finance Background			
Log(Ret) (z)	0.035***	0.039***	0.034***	-0.012***	-0.027***	-0.016***
	(0.002)	(0.003)	(0.003)	(0.003)	(0.005)	(0.005)
Investor Type	0.000	-0.001	0.001	-0.002	-0.001	0.003
	(0.001)	(0.002)	(0.002)	(0.002)	(0.005)	(0.004)
Investor Type × Log(Ret) (z)	0.002*	0.003*	0.003	0.011***	0.008	0.018**
	(0.001)	(0.002)	(0.003)	(0.004)	(0.008)	(0.007)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Outcome SD	0.076	0.074	0.072	0.634	0.647	0.619
R2	0.229	0.217	0.130	0.000	0.001	0.000
Observations	7,172	3,732	3,440	327,132	168,334	158,798
			Low Wealth			
Log(Ret) (z)	0.036***	0.041***	0.035***	-0.006**	-0.016***	-0.008*
	(0.001)	(0.003)	(0.002)	(0.002)	(0.004)	(0.005)
Investor Type	-0.001	-0.000	0.001	-0.003	-0.001	-0.002
	(0.001)	(0.002)	(0.003)	(0.002)	(0.004)	(0.004)
Investor Type × Log(Ret) (z)	-0.003***	-0.005**	-0.002	-0.004	-0.007	-0.004
	(0.001)	(0.002)	(0.003)	(0.003)	(0.006)	(0.005)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Outcome SD	0.083	0.078	0.084	0.584	0.579	0.589
R2	0.174	0.180	0.089	0.000	0.001	0.000
Observations	7,172	3,732	3,440	328,355	168,889	159,466
			Young			
Log(Ret) (z)	0.036***	0.040***	0.035***	-0.007**	-0.018***	-0.010**
	(0.001)	(0.003)	(0.002)	(0.003)	(0.007)	(0.005)
Investor Type	-0.001	-0.001	-0.001	-0.001	0.002	0.002
	(0.001)	(0.002)	(0.002)	(0.002)	(0.004)	(0.003)
Investor Type × Log(Ret) (z)	-0.002*	-0.001	-0.003	-0.001	-0.007	0.002
	(0.001)	(0.002)	(0.002)	(0.003)	(0.007)	(0.004)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Outcome SD	0.076	0.074	0.072	0.499	0.520	0.475
R2	0.218	0.209	0.119	0.000	0.001	0.000
Observations	7,172	3,732	3,440	330,496	169,981	160,515
			Ever Guru			
Log(Ret) (z)	0.035***	0.039***	0.034***	-0.010***	-0.020***	-0.015***
	(0.001)	(0.003)	(0.002)	(0.003)	(0.005)	(0.005)
Investor Type	0.000	-0.001	0.005	-0.002	0.001	-0.002
	(0.002)	(0.004)	(0.004)	(0.002)	(0.004)	(0.004)
Investor Type × Log(Ret) (z)	0.006***	0.005*	0.012***	0.006*	0.003	0.008
	(0.002)	(0.003)	(0.003)	(0.004)	(0.007)	(0.006)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Outcome SD	0.099	0.100	0.094	0.496	0.491	0.501
R2	0.150	0.125	0.097	0.001	0.001	0.001
Observations	7,160	3,726	3,434	322,315	165,920	156,395

Panel B

	Log(active share change)					
	Cryptos			Top 200 Stocks		
	All	Ret>0	Ret≤0	All	Ret>0	Ret≤0
	(1)	(2)	(3)	(4)	(5)	(6)
			Female			
Log(Ret) (z)	-0.001	-0.000	0.000	-0.034***	-0.048***	-0.038***
	(0.002)	(0.003)	(0.003)	(0.002)	(0.004)	(0.005)
Investor Type	0.000	0.005	-0.005	-0.006*	-0.013*	-0.001
	(0.002)	(0.003)	(0.004)	(0.004)	(0.007)	(0.007)
Investor Type × Log(Ret) (z)	-0.002	-0.001	-0.010*	-0.016***	-0.012	-0.012
	(0.002)	(0.004)	(0.005)	(0.006)	(0.011)	(0.012)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Outcome SD	0.087	0.091	0.083	0.834	0.873	0.791
R2	0.012	0.012	0.021	0.003	0.002	0.003
Observations	7,149	3,721	3,428	303,049	155,969	147,080
			Finance Background			
Log(Ret) (z)	-0.002	-0.001	-0.001	-0.037***	-0.053***	-0.041***
	(0.002)	(0.003)	(0.004)	(0.003)	(0.005)	(0.005)
Investor Type	0.000	-0.001	-0.000	-0.003	-0.003	0.002
	(0.001)	(0.002)	(0.002)	(0.002)	(0.005)	(0.004)
Investor Type × Log(Ret) (z)	0.002	0.003	0.002	0.010**	0.008	0.018**
	(0.002)	(0.002)	(0.004)	(0.004)	(0.008)	(0.007)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Outcome SD	0.064	0.062	0.066	0.634	0.648	0.619
R2	0.012	0.015	0.018	0.003	0.003	0.003
Observations	7,172	3,732	3,440	327,132	168,334	158,798
			Low Wealth			
Log(Ret) (z)	-0.001	0.001	0.000	-0.031***	-0.042***	-0.033***
	(0.002)	(0.003)	(0.003)	(0.002)	(0.004)	(0.005)
Investor Type	0.001	0.002	0.002	-0.004*	-0.002	-0.005
	(0.002)	(0.003)	(0.003)	(0.002)	(0.004)	(0.004)
Investor Type × Log(Ret) (z)	-0.004*	-0.005*	-0.003	-0.004	-0.007	-0.003
	(0.002)	(0.003)	(0.004)	(0.003)	(0.006)	(0.005)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Outcome SD	0.073	0.068	0.079	0.584	0.579	0.589
R2	0.014	0.020	0.013	0.003	0.003	0.003
Observations	7,172	3,732	3,440	328,355	168,889	159,466
			Young			
Log(Ret) (z)	-0.001	-0.000	-0.000	-0.032***	-0.044***	-0.035***
	(0.002)	(0.003)	(0.003)	(0.003)	(0.007)	(0.005)
Investor Type	0.001	-0.000	0.001	-0.001	0.002	0.002
	(0.001)	(0.002)	(0.003)	(0.002)	(0.004)	(0.003)
Investor Type × Log(Ret) (z)	-0.001	0.000	0.000	-0.001	-0.007	0.003
	(0.002)	(0.002)	(0.003)	(0.003)	(0.007)	(0.004)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Outcome SD	0.064	0.063	0.066	0.499	0.520	0.476
R2	0.014	0.016	0.020	0.004	0.005	0.004
Observations	7,172	3,732	3,440	330,496	169,981	160,515
			Ever Guru			
Log(Ret) (z)	-0.002	-0.001	0.000	-0.035***	-0.047***	-0.040***
	(0.002)	(0.003)	(0.003)	(0.002)	(0.005)	(0.005)
Investor Type	0.001	-0.001	0.005	-0.005***	-0.003	-0.005
	(0.002)	(0.004)	(0.004)	(0.002)	(0.004)	(0.004)
Investor Type × Log(Ret) (z)	-0.004*	-0.003	-0.001	0.005	0.003	0.007
	(0.003)	(0.003)	(0.006)	(0.004)	(0.007)	(0.006)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Outcome SD	0.091	0.092	0.089	0.497	0.492	0.502
R2	0.006	0.007	0.008	0.005	0.005	0.005
Observations	7,138	3,711	3,427	322,315	165,920	156,395

Table 7. **Active vs. Non-active Investors**

In this table we examine whether active investors trade differently than non-active investors. We generate a representative investor, by cumulating trades, net inflows, and wealth, across all investors who participated on the platform at date t. An investor is defined as active if she traded any asset in the prior 7 days, and as inactive if she didn't trade any asset in the prior 30 days. We only look at investors who have been on eToro for at least 30 days, and have traded both cryptos and stocks during their tenure there. $Log(\text{Total Share Change}_t)$ and $Log(\text{Active Share Change}_t)$ are defined as in Table 3. Controls include lagged 1 week, 1 moth, 3 month, and 6 month cumulative returns for total and active share change regressions, as well as returns on wealth and net inflows, for active share change. *Cryptos* are BTC, XRP, and ETH. For the list of the top 200 stocks by eToro trading, refer to Table A1. Log returns are standardized within asset class across the entire time period, and denoted with (z). Standard errors are clustered at the date level and reported in parentheses. Statistical significance is denoted at the ten, five, and one percent levels by *, **, and ***, respectively.

Panel A: Active Investors

	Log(total share change)					
	Cryptos			Top 200 Stocks		
	All	Ret>0	Ret≤0	All	Ret>0	Ret≤0
	(1)	(2)	(3)	(4)	(5)	(6)
Log(Ret) (z)	0.036***	0.042***	0.033***	-0.019***	-0.032***	-0.021***
	(0.002)	(0.003)	(0.003)	(0.003)	(0.005)	(0.005)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Outcome SD	0.098	0.098	0.092	0.478	0.485	0.471
R2	0.141	0.132	0.066	0.002	0.002	0.002
Observations	3,586	1,866	1,720	167,305	86,002	81,303

	Log(active share change)					
	Cryptos			Top 200 Stocks		
	All	Ret>0	Ret≤0	All	Ret>0	Ret≤0
	(1)	(2)	(3)	(4)	(5)	(6)
Log(Ret) (z)	-0.002	-0.001	-0.002	-0.044***	-0.058***	-0.047***
	(0.001)	(0.009)	(0.008)	(0.003)	(0.005)	(0.005)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Outcome SD	0.097	0.099	0.095	0.480	0.486	0.472
R2	0.127	0.135	0.126	0.010	0.008	0.009
Observations	3,586	1,866	1,720	167,305	86,002	81,303

Panel B: Non-active Investors

	Log(total share change)					
	Cryptos			Top 200 Stocks		
	All	Ret>0	Ret≤0	All	Ret>0	Ret≤0
	(1)	(2)	(3)	(4)	(5)	(6)
Log(Ret) (z)	0.045***	0.069***	0.031***	0.023***	0.011	0.027***
	(0.007)	(0.017)	(0.006)	(0.005)	(0.009)	(0.008)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Outcome SD	0.215	0.254	0.162	1.177	1.173	1.182
R2	0.044	0.052	0.019	0.000	0.000	0.000
Observations	3,546	1,847	1,699	131,419	67,758	63,661

	Log(active share change)					
	Cryptos			Top 200 Stocks		
	All	Ret>0	Ret≤0	All	Ret>0	Ret≤0
	(1)	(2)	(3)	(4)	(5)	(6)
Log(Ret) (z)	-0.002	0.023	-0.013*	-0.005	-0.016*	0.000
	(0.009)	(0.019)	(0.007)	(0.005)	(0.009)	(0.008)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Outcome SD	0.213	0.250	0.162	1.179	1.175	1.184
R2	0.020	0.029	0.024	0.004	0.004	0.004
Observations	3,542	1,845	1,697	131,419	67,758	63,661

Table 8. **Existing Users**

In this table we examine how users trade to have been active on the platform for at least 90 days. We generate a representative investor, by cumulating trades, net inflows, and wealth, across all investors who participated on the platform at date t. We focus on investors who have been active on eToro for at least 90 days prior to day t. $Log(\text{Total Share Change}_t)$ and $Log(\text{Active Share Change}_t)$ are defined as in Table 3. Controls include lagged 1 week, 1 moth, 3 month, and 6 month cumulative returns for total and active share change regressions, as well as returns on wealth and net inflows, for active share change. *Cryptos* are BTC, XRP, and ETH. For the list of the top 200 stocks by eToro trading, refer to Table A1. Log returns are standardized within asset class across the entire time period, and denoted with (z). Standard errors are clustered at the date level and reported in parentheses. Statistical significance is denoted at the ten, five, and one percent levels by *, **, and ***, respectively.

Panel A

	Log(total share change)					
	Cryptos			Top 200 Stocks		
	All	Ret>0	Ret≤0	All	Ret>0	Ret≤0
	(1)	(2)	(3)	(4)	(5)	(6)
Log(Ret) (z)	0.035***	0.039***	0.035***	-0.011***	-0.026***	-0.013***
	(0.001)	(0.003)	(0.002)	(0.002)	(0.004)	(0.005)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Outcome SD	0.071	0.065	0.071	0.369	0.367	0.371
R2	0.247	0.266	0.128	0.001	0.003	0.001
Observations	3,586	1,866	1,720	168,165	86,481	81,684

Panel B

	Log(active share change)					
	Cryptos			Top 200 Stocks		
	All	Ret>0	Ret≤0	All	Ret>0	Ret≤0
	(1)	(2)	(3)	(4)	(5)	(6)
Log(Ret) (z)	-0.003*	-0.001	-0.003	-0.036***	-0.052***	-0.039***
	(0.002)	(0.003)	(0.002)	(0.002)	(0.004)	(0.005)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Outcome SD	0.071	0.065	0.071	0.369	0.367	0.371
R2	0.013	0.010	0.022	0.010	0.010	0.009
Observations	3,586	1,866	1,720	168,165	86,481	81,684

Table 9. **Individual Investors**

In this table we examine how contemporaneous and lagged returns affect individuals' trading behavior. We keep the top 50% of traders by the number of days they traded in stocks/cryptos on eToro. *Log*(Total Share Change$_t$) and *Log*(Active Share Change$_t$) are defined as in Table 3. Controls include lagged 1 week, 1 moth, 3 month, and 6 month cumulative returns for total and active share change regressions, as well as returns on wealth and net inflows, for active share change. *Cryptos* are BTC, XRP, and ETH. For the list of the top 200 stocks by eToro trading, refer to Table A1. *Log*(*Ret*) is defined as log of return on day t, and *Log*(CR past 1 week) is defined as the cumulative return over the past 7 days. In Panel B *Log*(Wealth Ret$_t$) is defined as $\log([Wealth_t - NetInflows_t]/Wealth_{t-1})$, and log(Ret Net Inflows) is defined as $\log(Wealth_t/Wealth_{t-1}) - \log((Wealth_t - NetInflows_t)/Wealth_{t-1})$. All columns include instrument, individual, and date fixed effects. Standard errors are clustered at the date and individual investor level and reported in parentheses. Statistical significance is denoted at the ten, five, and one percent levels by *, **, and ***, respectively.

Panel A

	Log(total share change)					
	Cryptos			Top 200 Stocks		
	All	Ret>0	Ret≤0	All	Ret>0	Ret≤0
	(1)	(2)	(3)	(4)	(5)	(6)
Log(Ret) (z)	0.035***	0.023***	0.045***	-0.013***	-0.048***	0.012**
	(0.003)	(0.007)	(0.005)	(0.003)	(0.005)	(0.005)
Log(CR past 1 week) (z)	0.001	0.008**	-0.004	-0.010***	-0.017***	-0.003**
	(0.002)	(0.004)	(0.004)	(0.001)	(0.002)	(0.001)
Log(CR past 1 month) (z)	0.006**	0.006*	0.007	-0.000	-0.003**	0.001
	(0.003)	(0.003)	(0.004)	(0.001)	(0.001)	(0.001)
Log(CR past 3 months) (z)	-0.001	-0.003	0.000	0.003***	0.002	0.004***
	(0.002)	(0.003)	(0.002)	(0.001)	(0.001)	(0.002)
Log(CR past 6 months) (z)	0.000	0.001	-0.003	0.002*	0.001	0.001
	(0.002)	(0.003)	(0.002)	(0.001)	(0.001)	(0.001)
Outcome SD	1.010	1.064	0.953	1.380	1.361	1.399
R2	0.001	0.002	0.001	0.001	0.001	0.001
Observations	39,097,978	19,494,612	19,603,366	27,353,902	14,261,781	13,092,121

Panel B

	Log(active share change)					
	Cryptos			Top 200 Stocks		
	All	Ret>0	Ret≤0	All	Ret>0	Ret≤0
	(1)	(2)	(3)	(4)	(5)	(6)
Log(Ret) (z)	-0.012***	-0.021***	-0.004	-0.031***	-0.068***	-0.007
	(0.003)	(0.008)	(0.005)	(0.003)	(0.005)	(0.005)
Log(CR past 1 week) (z)	0.002	0.008**	-0.003	-0.010***	-0.019***	-0.002
	(0.002)	(0.004)	(0.004)	(0.001)	(0.002)	(0.001)
Log(CR past 1 month) (z)	0.007***	0.007**	0.006	-0.001	-0.006***	0.002*
	(0.003)	(0.003)	(0.004)	(0.001)	(0.001)	(0.001)
Log(CR past 3 months) (z)	-0.001	-0.002	0.001	0.002**	-0.000	0.006***
	(0.002)	(0.003)	(0.002)	(0.001)	(0.001)	(0.002)
Log(CR past 6 months) (z)	0.001	0.001	-0.003	0.002**	0.000	0.003**
	(0.002)	(0.003)	(0.002)	(0.001)	(0.001)	(0.001)
Log(Ret Wealth) (z)	0.050***	0.053***	0.046***	0.031***	0.031***	0.032***
	(0.002)	(0.002)	(0.003)	(0.001)	(0.002)	(0.002)
Log(Ret Net Inflows) (z)	0.061***	0.064***	0.056***	0.036***	0.035***	0.037***
	(0.002)	(0.002)	(0.004)	(0.001)	(0.002)	(0.002)
Outcome SD	1.010	1.064	0.953	1.376	1.356	1.397
R2	0.003	0.007	0.007	0.002	0.008	0.007
Observations	39,097,443	19,493,816	19,602,536	27,352,640	14,259,971	13,090,327

Table 10. **Before versus After Crash – Active Investors**

In this table we examine whether investors traded differently after the 2018 crypto crash, relative to before. We generate a representative investor, by cumulating trades, net inflows, and wealth, across all investors who participated on the platform at date t. We focus on active investors, who traded any asset in the prior 7 days and who has been on eToro for at least 30 days, and have traded both cryptos and stocks during their tenure there. *After Crash* is an indicator variable equal to 1 if the date is after January 1, 2018 and 0 before. $Log(\text{Total Share Change}_t)$ and $Log(\text{Active Share Change}_t)$ are defined as in Table 3. Controls include lagged 1 week, 1 moth, 3 month, and 6 month cumulative returns for total and active share change regressions, as well as returns on wealth and net inflows, for active share change. *Cryptos* are BTC, XRP, and ETH. For the list of the top 200 stocks by eToro trading, refer to Table A1. Log returns are standardized within asset class across the entire time period, and denoted with (z). Standard errors are clustered at the date level and reported in parentheses. Statistical significance is denoted at the ten, five, and one percent levels by *, **, and ***, respectively.

Panel A

	Log(total share change)					
	Cryptos			Top 200 Stocks		
	All	Ret>0	Ret≤0	All	Ret>0	Ret≤0
	(1)	(2)	(3)	(4)	(5)	(6)
After Crash	-0.004	-0.005	-0.008	-0.004	-0.009	-0.016**
	(0.005)	(0.007)	(0.008)	(0.004)	(0.007)	(0.007)
After Crash × Log(Ret) (z)	-0.006*	-0.005	-0.009	-0.002	0.014	-0.017*
	(0.003)	(0.005)	(0.007)	(0.006)	(0.011)	(0.010)
Log(Ret) (z)	0.040***	0.046***	0.036***	-0.017***	-0.038***	-0.011
	(0.003)	(0.004)	(0.006)	(0.004)	(0.009)	(0.007)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Outcome SD	0.095	0.099	0.085	0.494	0.510	0.477
R2	0.161	0.145	0.084	0.001	0.002	0.002
Observations	3,586	1,866	1,720	168,087	86,415	81,672

Panel B

	Log(active share change)					
	Cryptos			Top 200 Stocks		
	All	Ret>0	Ret≤0	All	Ret>0	Ret≤0
	(1)	(2)	(3)	(4)	(5)	(6)
After Crash	-0.001	-0.000	-0.005	-0.021***	-0.015**	-0.041***
	(0.005)	(0.007)	(0.008)	(0.004)	(0.007)	(0.007)
After Crash × Log(Ret) (z)	-0.014***	-0.013**	-0.013*	-0.003	0.013	-0.019*
	(0.003)	(0.005)	(0.007)	(0.006)	(0.011)	(0.010)
Log(Ret) (z)	-0.007**	-0.003	-0.012*	-0.042***	-0.063***	-0.037***
	(0.003)	(0.005)	(0.006)	(0.004)	(0.009)	(0.007)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Outcome SD	0.094	0.099	0.088	0.495	0.510	0.478
R2	0.151	0.151	0.166	0.009	0.007	0.011
Observations	3,586	1,866	1,720	168,087	86,415	81,672

Table 11. **Stock Characteristics**

In this table we examine whether there is heterogeneity in how investors trade stocks, based on the stocks characteristics. We generate a representative investor, by cumulating trades, net inflows, and wealth, across all investors who participated on the platform at date t. We only look at investors who have traded both cryptos and stocks during their tenure at eToro. *Log*(Total Share Change$_t$) and *Log*(Active Share Change$_t$) are defined as in Table 3. Controls include lagged 1 week, 1 moth, 3 month, and 6 month cumulative returns for total and active share change regressions, as well as returns on wealth and net inflows, for active share change. For the list of the top 200 stocks by eToro trading, refer to Table A1. *Max Return Month t-1* is defined as the maximum daily return in the prior calendar month. *Return Volatility* is defined as the standard deviation of daily returns over the past calendar month. *Return Skewness* is defined as skewness of daily returns over the past calendar month. *Young Firm* is defined as firm that is less than a year old. *Gross Profitability* is revenues minus cost of goods sold divided by lagged total assets. Log returns are standardized within asset class across the entire time period, and denoted with (z). Standard errors are clustered at the date level and reported in parentheses. Statistical significance is denoted at the ten, five, and one percent levels by *, **, and ***, respectively.

	Log(Total Share Change)			Log(Active Share Change)		
	All	Ret>0	Ret≤0	All	Ret>0	Ret≤0
	(1)	(2)	(3)	(4)	(5)	(6)
			Max. Return Month (t-1)			
Stock Characteristics	0.030	-0.086	0.058	0.018	-0.088	0.038
	(0.038)	(0.057)	(0.066)	(0.037)	(0.057)	(0.067)
Stock Characteristics × Log(Ret) (z)	0.054*	0.190***	0.052	0.049	0.194***	0.041
	(0.031)	(0.056)	(0.059)	(0.031)	(0.055)	(0.059)
Log(Ret) (z)	-0.018***	-0.040***	-0.025***	-0.040***	-0.065***	-0.048***
	(0.003)	(0.006)	(0.007)	(0.003)	(0.006)	(0.007)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Outcome SD	0.385	0.392	0.377	0.386	0.393	0.378
R2	0.002	0.003	0.003	0.010	0.010	0.011
Observations	145,673	75,212	70,461	145,673	75,212	70,461
			Return Volatility			
Stock Characteristics	-0.016	-0.380**	-0.098	-0.073	-0.454**	-0.142
	(0.120)	(0.173)	(0.224)	(0.125)	(0.182)	(0.227)
Stock Characteristics × Log(Ret) (z)	-0.152	0.465***	-0.290	-0.201	0.449***	-0.343
	(0.125)	(0.175)	(0.271)	(0.126)	(0.174)	(0.273)
Log(Ret) (z)	-0.009*	-0.041***	-0.012	-0.031***	-0.065***	-0.034***
	(0.005)	(0.008)	(0.010)	(0.005)	(0.008)	(0.010)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Outcome SD	0.385	0.393	0.377	0.386	0.393	0.378
R2	0.002	0.003	0.003	0.010	0.009	0.011
Observations	145,439	75,100	70,339	145,439	75,100	70,339
			Return Skewness			
Stock Characteristics	-0.000	0.001	-0.002	-0.000	0.001	-0.002
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)
Stock Characteristics × Log(Ret) (z)	-0.003***	-0.003	-0.004*	-0.003***	-0.003	-0.004**
	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)
Log(Ret) (z)	-0.013***	-0.025***	-0.020***	-0.036***	-0.049***	-0.043***
	(0.002)	(0.005)	(0.004)	(0.002)	(0.005)	(0.004)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Outcome SD	0.385	0.392	0.377	0.386	0.393	0.378
R2	0.002	0.003	0.003	0.010	0.009	0.011
Observations	145,673	75,212	70,461	145,673	75,212	70,461
			Firm Age <= 1 year			
Stock Characteristics	0.012*	-0.002	0.032**	0.015**	0.001	0.034**
	(0.006)	(0.013)	(0.013)	(0.006)	(0.014)	(0.014)
Stock Characteristics × Log(Ret) (z)	-0.003	0.005	0.010	-0.005	0.004	0.008
	(0.008)	(0.015)	(0.015)	(0.008)	(0.016)	(0.015)
Log(Ret) (z)	-0.014***	-0.026***	-0.022***	-0.037***	-0.050***	-0.046***
	(0.002)	(0.005)	(0.005)	(0.002)	(0.005)	(0.005)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Outcome SD	0.385	0.392	0.377	0.386	0.393	0.378
R2	0.001	0.002	0.003	0.009	0.009	0.011
Observations	145,673	75,212	70,461	145,673	75,212	70,461
			Gross Profitability			
Stock Characteristics	-0.002	0.008	-0.009	-0.001	0.009	-0.009
	(0.003)	(0.008)	(0.008)	(0.003)	(0.008)	(0.008)
Stock Characteristics × Log(Ret) (z)	-0.005	-0.013	-0.008	-0.006	-0.014	-0.008
	(0.005)	(0.011)	(0.010)	(0.005)	(0.011)	(0.010)
Log(Ret) (z)	-0.012***	-0.021***	-0.019***	-0.035***	-0.046***	-0.043***
	(0.003)	(0.006)	(0.006)	(0.003)	(0.006)	(0.006)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Outcome SD	0.386	0.394	0.378	0.387	0.394	0.378
R2	0.001	0.003	0.003	0.009	0.009	0.011
Observations	143,187	73,964	69,223	143,187	73,964	69,223

Table 12. **Stock Trading around Earnings Announcements**

In this table we examine whether investors trade differently around earnings announcements than outside of earnings period. We generate a representative investor, by cumulating trades, net inflows, and wealth, across all investors who participated on the platform at date t. We only look at investors who have traded both cryptos and stocks during their tenure at eToro. *EA Days* are defined as 3 days before and 5 days after an earnings announcement. *Non EA Days* are all the other days. *Log*(Total Share Change$_t$) and *Log*(Active Share Change$_t$) are defined as in Table 3. Controls include lagged 1 week, 1 moth, 3 month, and 6 month cumulative returns for total and active share change regressions, as well as returns on wealth and net inflows, for active share change. For the list of the top 200 stocks by eToro trading, refer to Table A1. Log returns are standardized within asset class across the entire time period, and denoted with (z). Standard errors are clustered at the date level and reported in parentheses. Statistical significance is denoted at the ten, five, and one percent levels by *, **, and ***, respectively.

Panel A

	Log(total share change)					
	EA Days			Non EA Days		
	All	Ret>0	Ret≤0	All	Ret>0	Ret≤0
	(1)	(2)	(3)	(4)	(5)	(6)
Log(Ret) (z)	-0.035***	-0.066***	-0.039***	-0.001	-0.008*	-0.003
	(0.006)	(0.011)	(0.011)	(0.002)	(0.004)	(0.004)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Outcome SD	0.517	0.527	0.506	0.357	0.362	0.353
R2	0.010	0.017	0.011	0.000	0.000	0.000
Observations	23,732	11,907	11,825	144,895	74,867	70,028

Panel B

	Log(active share change)					
	EA Days			Non EA Days		
	All	Ret>0	Ret≤0	All	Ret>0	Ret≤0
	(1)	(2)	(3)	(4)	(5)	(6)
Log(Ret) (z)	-0.062***	-0.093***	-0.066***	-0.025***	-0.033***	-0.027***
	(0.006)	(0.011)	(0.011)	(0.002)	(0.004)	(0.004)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Outcome SD	0.522	0.531	0.511	0.357	0.361	0.352
R2	0.030	0.032	0.032	0.004	0.004	0.003
Observations	23,732	11,907	11,825	144,895	74,867	70,028

Appendix: Supplemental Tables and Figures for "Are Cryptos Different?"

Table A1. **200 Firms Examined in the paper**

Company name	Num Trades	Company name	Num Trades
Tesla Motors, Inc.	725,166	Ak Steel Holding Corp	14,074
Amazon	647,683	American Airlines Group Inc	13,814
Apple	643,946	Ford Motor Co	13,755
Advanced Micro Devices Inc	526,271	Delta Air Lines Inc (DE)	13,685
Facebook	523,073	Agilent Technologies Inc	13,661
Alphabet	458,467	Zynga	13,500
Netflix, Inc.	398,644	Pfizer	13,355
Micron Technology, Inc.	233,096	Home Depot Inc	13,105
Microsoft	199,072	GoDaddy Inc.	13,050
Cronos Group Inc	163,039	JC Penney Co Inc	12,900
Twitter	159,169	3M	12,857
Shopify Inc.	133,151	General Motors Co	12,514
Beyond Meat Inc.	124,045	Fitbit	12,435
Zynerba Pharmaceuticals Inc	121,397	Halliburton Co	12,400
PayPal Holdings	117,506	Uniti Group Inc	12,195
Square, Inc.	109,591	PepsiCo	12,068
Electronic Arts, Inc.	109,146	Vipshop	12,052
Activision Blizzard, Inc.	107,017	Maxlinear Inc	11,906
Aurora Cannabis Inc	104,928	Abercrombie & Fitch Company	11,671
Walt Disney	92,354	Zendesk	11,623
Western Digital Corporation	86,264	Gilead Sciences Inc	11,411
Boeing	79,170	Etsy Inc	11,371
First Solar, Inc.	78,712	Community Health Systems Inc	11,147
Intel	70,557	Luckin Coffee Inc.	11,082
Mastercard	70,240	Wells Fargo & Co	11,060
Visa	68,358	Mattel Inc	11,003
Baidu, Inc.	65,099	Biogen Inc	10,971
Applied Materials Inc	63,618	Signet Jewelers Limited (us)	10,717
Adobe Systems Inc	58,455	Vale SA	10,682
Overstock.com, Inc.	53,640	Foot Locker Inc	10,664
McDonalds	52,851	Philip Morris International Inc	10,623
Corbus Pharmaceuticals Holding	52,368	GNC Holdings Inc	10,608
Spotify	47,274	Macys Inc	10,592
Dropbox Inc	46,363	Match Group, Inc	10,162
GoPro Inc	40,599	Avon Products Inc	10,161
SolarEdge Technologies	37,963	Vodafone Group	9,944
NIKE	37,524	Dean Foods Co	9,699
General Electric Co	36,885	Alaska Air Group Inc	9,576
Salesforce.com Inc	35,588	CyberArk	9,394
Cisco	33,650	Exxon-Mobil	9,362
Coca-Cola	33,237	Cloudflare	9,195
Hertz Global Holdings Inc	32,276	Barrick Gold	9,140
Insys Therapeutics Inc	31,862	Costco Wholesale Corp	9,105
Sony	31,725	Wayfair Inc.	8,869
Qualcomm Inc	31,415	Autohome	8,680
Ascena Retail Group Inc	31,176	VMware	8,464
Deutsche-Bank	29,733	Chipotle Mexican Grill Inc	8,283
Aphria Inc.	29,362	Fiverr International	8,281
Autodesk, Inc.	29,292	Raytheon Co	8,178
Wal-Mart	29,236	BlackRock Inc	8,168
Tilray, Inc.	28,927	Best Buy Co Inc	8,162
Frontier Communications Corporation	28,766	Owens & Minor Inc	8,070
Pinterest Inc	27,896	Illumina	7,789
GW Pharmaceuticals Plc	26,973	Deere & Co	7,743
Yandex NV	26,583	Whiting Petroleum Corp	7,739
NetEase	26,320	Target Corp	7,711
eBay	25,765	Banco Santander SA (US)	7,684
Take Two Interactive Software Inc	25,720	Wynn Resorts Ltd	7,679
Bank of America Corp	25,432	Allergan PLC	7,651
TripAdvisor Inc	25,286	Vertex Pharmaceuticals Incorporated	7,501
JPMorgan Chase & Co	24,781	Texas Instruments Inc	7,468
Ferrari NV	24,135	Hasbro Inc	7,442
Caterpillar	22,954	Palo Alto Networks	7,335
Intercept Pharma	22,797	Transocean LTD	7,266
MercadoLibre	22,521	Cigna Corp	7,260
Petroleo Brasileiro	22,510	Incyte Corp.	7,202
Nio Inc.	22,108	FMC Corp	7,049
Intellia Therapeutics Inc	21,812	Skyworks Solutions	6,943
Chesapeake Energy Corp	21,380	Walgreens Boots Alliance Inc	6,841
Akorn	21,346	Tiffany & Co	6,523
Hewlett Packard	20,985	Expedia Inc Del	6,477
Slack Technologies Inc	20,830	Altria Group Inc	6,471
Editas Medicine Inc	20,569	New Relic	6,454
Citigroup	20,175	Abbott Laboratories	6,383
Goldman Sachs Group Inc	19,929	Chevron	6,315
Bitauto Holdings Limited	19,623	HubSpot	6,313
Roku Inc	19,507	Dollar Tree Inc	6,274
The Kraft Heinz Company	18,828	FireEye	6,262
Southwestern Energy Co	18,686	Regeneron Pharmaceuticals	6,254
Lyft Inc.	18,405	Tech Data Corp	6,147
GameStop Corp New	18,386	Freeport-McMoRan Inc	6,044
CVS Health Corp	18,361	Gap, Inc.	5,979
Superior Energy Services Inc	17,739	BlackStone Group LP	5,975
Canopy Growth Corp	17,498	Teva Pharmaceutical Industries ADR	5,964
Johnson & Johnson	17,120	Red Hat	5,953
Puma Biotechnology Inc	16,913	Bed Bath & Beyond Inc	5,891
United States Steel Corp	16,886	Synaptics Inc.	5,850
UnitedHealth	16,258	Shake Shack Inc	5,787
Rite Aid Corp	16,170	Bristol-Myers Squibb Co	5,628
Sangamo Biosciences Inc	16,024	Wix.com Ltd	5,522
Weatherford International plc	15,949	Tenet Healthcare Corp	5,517
AbbVie Inc	15,746	Ipg Photonics Corp.	5,510
Under Armour	15,619	Big Lots Inc	5,489
Globalstar	15,304	United Natural Foods Inc	5,451
Nokia Corp.	15,217	Urban Outfitters Inc.	5,437
Procter & Gamble Co	15,214	CommScope Holding Co Inc	5,431
Cara Therapeutics	14,804	Amgen Inc	5,368
American Express CO	14,636	The Chemours	5,360
Celgene Corp	14,594	Estee Lauder Companies Inc	5,355
Lockheed Martin Corporation	14,452	Crowdstrike Holdings	5,254

Table A2. **Before versus After Crash: Investor Characteristics**

In this table we examine whether there is heterogeneity in how investors changed their trading around the crypto crash across investor characteristics. We generate two representative investors, by cumulating trades, net inflows, and wealth, across all investors who participated on the platform at date t, based on whether the investors have a certain characteristics or they don't. We only look at investors who have traded both cryptos and stocks during their tenure at eToro. Investor characteristics are defined in Table 6. *After Crash* is an indicator variable equal to 1 if the date is after January 1, 2018 and 0 before. *Log*(Total Share Change$_t$) and *Log*(Active Share Change$_t$) are defined as in Table 3. Controls include lagged 1 week, 1 moth, 3 month, and 6 month cumulative returns for total and active share change regressions, as well as returns on wealth and net inflows, for active share change. *Cryptos* are BTC, XRP, and ETH. For the list of the top 200 stocks by eToro trading, refer to Table A1. Standard errors are clustered at the date level and reported in parentheses. Statistical significance is denoted at the ten, five, and one percent levels by *, **, and ***, respectively.

Panel A

	Log(total share change)					
	Cryptos			Top 200 Stocks		
	All	Ret>0	Ret≤0	All	Ret>0	Ret≤0
	(1)	(2)	(3)	(4)	(5)	(6)
			Female			
After Crash × Investor Type × Log(Ret) (z)	0.001	0.002	0.003	0.023	0.071**	-0.003
	(0.003)	(0.004)	(0.006)	(0.015)	(0.031)	(0.027)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Outcome SD	0.096	0.098	0.087	0.834	0.873	0.791
R2	0.157	0.130	0.096	0.001	0.001	0.001
Observations	7,167	3,732	3,435	303,049	155,969	147,080
			Finance Background			
After Crash × Investor Type × Log(Ret) (z)	0.000	0.001	0.002	-0.017*	0.005	-0.031*
	(0.003)	(0.003)	(0.009)	(0.009)	(0.019)	(0.016)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Outcome SD	0.076	0.074	0.072	0.634	0.647	0.619
R2	0.242	0.232	0.144	0.000	0.001	0.001
Observations	7,172	3,732	3,440	327,132	168,334	158,798
			Low Wealth			
After Crash × Investor Type × Log(Ret) (z)	0.002	0.005	-0.004	0.011	0.033**	-0.003
	(0.003)	(0.004)	(0.008)	(0.007)	(0.015)	(0.011)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Outcome SD	0.083	0.078	0.084	0.584	0.579	0.589
R2	0.185	0.195	0.100	0.000	0.001	0.001
Observations	7,172	3,732	3,440	328,355	168,889	159,466
			Young			
After Crash × Investor Type × Log(Ret) (z)	0.002	0.001	0.005	0.008	0.008	0.002
	(0.002)	(0.003)	(0.004)	(0.007)	(0.017)	(0.011)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Outcome SD	0.076	0.074	0.072	0.499	0.520	0.475
R2	0.231	0.225	0.134	0.001	0.001	0.001
Observations	7,172	3,732	3,440	330,496	169,981	160,515
			Ever Guru			
After Crash × Investor Type × Log(Ret) (z)	0.018***	0.012***	0.018**	0.019*	0.044**	0.020
	(0.003)	(0.004)	(0.008)	(0.010)	(0.021)	(0.018)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Outcome SD	0.099	0.100	0.094	0.496	0.491	0.501
R2	0.155	0.131	0.112	0.001	0.002	0.001
Observations	7,160	3,726	3,434	322,315	165,920	156,395

Panel B

	Log(active share change)					
	Cryptos			Top 200 Stocks		
	All	Ret>0	Ret≤0	All	Ret>0	Ret≤0
	(1)	(2)	(3)	(4)	(5)	(6)
			Female			
After Crash × Investor Type × Log(Ret) (z)	0.002	-0.001	0.010	0.024	0.072**	-0.002
	(0.004)	(0.005)	(0.008)	(0.015)	(0.031)	(0.027)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Outcome SD	0.087	0.091	0.083	0.834	0.873	0.791
R2	0.018	0.019	0.038	0.003	0.003	0.003
Observations	7,149	3,721	3,428	303,049	155,969	147,080
			Finance Background			
After Crash × Investor Type × Log(Ret) (z)	-0.004	-0.003	-0.003	-0.018**	0.005	-0.031*
	(0.003)	(0.004)	(0.010)	(0.009)	(0.019)	(0.016)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Outcome SD	0.064	0.062	0.066	0.634	0.648	0.619
R2	0.019	0.025	0.029	0.003	0.003	0.004
Observations	7,172	3,732	3,440	327,132	168,334	158,798
			Low Wealth			
After Crash × Investor Type × Log(Ret) (z)	0.006*	0.008*	0.004	0.011	0.034**	-0.003
	(0.004)	(0.004)	(0.010)	(0.007)	(0.015)	(0.011)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Outcome SD	0.073	0.068	0.079	0.584	0.579	0.589
R2	0.021	0.034	0.023	0.003	0.004	0.004
Observations	7,172	3,732	3,440	328,355	168,889	159,466
			Young			
After Crash × Investor Type × Log(Ret) (z)	0.003	0.002	0.003	0.007	0.009	0.000
	(0.003)	(0.004)	(0.005)	(0.007)	(0.017)	(0.011)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Outcome SD	0.064	0.063	0.066	0.499	0.520	0.476
R2	0.021	0.028	0.030	0.005	0.005	0.005
Observations	7,172	3,732	3,440	330,496	169,981	160,515
			Ever Guru			
After Crash × Investor Type × Log(Ret) (z)	0.007*	0.003	0.007	0.019*	0.043**	0.022
	(0.004)	(0.004)	(0.011)	(0.010)	(0.021)	(0.018)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Outcome SD	0.091	0.092	0.089	0.497	0.492	0.502
R2	0.011	0.012	0.026	0.005	0.005	0.005
Observations	7,138	3,711	3,427	322,315	165,920	156,395