Are Cryptos Different?
Evidence from Retail Trading*

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Abstract

Trading in cryptocurrencies has grown rapidly over the last decade, primarily dominated by retail investors. Using a large dataset of 200,000 retail traders from eToro, we show that they have a different model of the underlying price dynamics in cryptocurrencies compared to other assets. Retail traders in our sample are contrarian in stocks and gold, yet the same traders follow a momentum strategy in cryptocurrencies. Individual characteristics do not explain the differences in how people trade cryptocurrencies versus stocks, suggesting that our results are orthogonal to differences in investor composition or clientele effects. Neither lack of cashflow information, inattention, or preference for lottery-like stocks explain our findings. We conjecture that retail investors hold a model of cryptocurrency prices, where positive returns increase the likelihood of future widespread adoption, which in turn will drive up asset prices.

Keywords: Cryptocurrencies, FinTech, Retail trading, Social finance

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1. Introduction

Cryptocurrency prices over the last decade have famously been marked by significant volatility and large boom and bust cycles, which have given rise to new investment mantras, such as FOMO — "fear of missing out" or FUD — "fear, uncertainty and doubt". Yet only little evidence exists on how investors trade in these new assets and how they form price expectations about cryptocurrencies.

Unlike traditional markets, trading in cryptocurrency markets has been dominated by retail investors. To study their investment behavior, we use a dataset of trades from 200,000 individual retail accounts on eToro, a large international retail discount brokerage, over the period from 2015-2019. eToro was one of the first platforms to allow retail investors to trade in cryptocurrencies along with traditional assets. This unique set up allows us to analyze differences in trading behavior across assets, holding constant individual preferences and circumstances.

We document a set of new facts by contrasting trading in cryptocurrencies with trading in stocks and commodities. First, we show a stark dichotomy in investors' trading strategies across different assets. Retail investors largely trade as contrarian in the stock market but in contrast they are willing to hold on to their crypto currency investments even after large changes in the returns which results in investors following momentum strategies when trading in crypto currencies. Importantly, these results even hold when we focus on the same investors trading across these different assets. Second, individual characteristics do not explain the differences in how people trade in cryptocurrencies versus stocks, suggesting that our results are not primarily driven by differences in investor composition or clientele effects. Finally, we show that our results are not the outcome of inattention, differential preferences for lottery-like assets, or lack of cash flow information about cryptocurrencies. We conjecture that retail investors have a model of cryptocurrency prices, where positive returns increase the likelihood of future widespread adoption, which in turn will drive up asset prices (and vice versa when prices go down). But they do not have the same price expectations for other more traditional assets where wider adoption has already happened.

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), who tie changes in portfolio shares allocated to different *asset classes* to investors' 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 and Viceira (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 that next period returns are positively correlated with this period's returns for a given asset, they will allocate a larger (smaller) share of their wealth to this asset, following a positive (negative) return or at a minimum they would not see a reason to to change their allocation to the asset. This type of re-balancing behavior would de facto lead investors in crypto to look like they are following a momentum strategy. Alternatively, if investors expect assets to be mean-reverting, they will trade contrarian, and allocate a smaller (larger) share of their wealth to this asset, following a positive (negative) return. 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 how investor's price expectation change as a function of price realizations. Several papers have tied survey expectations to changes in portfolio allocations even within individuals, and thus suggest a robust relationship between beliefs and portfolio allocations (e.g., Dominitz and Manski (2011), Kézdi and Willis (2011), and Giglio et al. (2021)).

To examine how investors react to contemporaneous and past returns in a given asset, we focus on the 200 most traded stocks on our retail platform, which comprise over 91% of trading in stocks on eToro (during our sample period). 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 because they are distracted or inattentive. As a result, the account-level portfolio share change analysis could be subject to a lot of spurious noise when studying the 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 idiosyncratic reasons, 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 all investors in a given cohort, will be picked up by our measure. This approach to data aggregation is conceptually similar to sorting individual stocks into factor portfolios in asset pricing tests which is routinely used to reduce the impact of idiosyncratic noise on parameter estimates. It does not mean that we are throwing away meaningful variation. In particular, we can also form cohorts at lower levels of aggregation, by allowing cohorts to vary by investor characteristics such as age, income, gender and many others, which allows us to study heterogeneity in trading behavior based on these individual differences without introducing a lot of noise. Finally, we also repeat the analysis at the individual level by looking at trading decisions of individuals in response to contemporaneous and lagged returns. We focus this analysis on the 50% of investors who are more active in our sample. The results across these different levels of data aggregation corroborate our analysis at the cohort level.

We start our analysis by regressing the log of the *total portfolio share* of a given asset on contemporaneous and past returns. 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. However, 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 portfolio 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 actively increasing it in stocks with negative contemporaneous returns. Similarly 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 is 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. [1] We find that investments in gold follow the same contrarian dynamics as in stocks. Investors reduce their total holdings and actively

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

rebalance out of gold when the price of gold increases and purchase gold when the price declines. Since cryptocurrencies have often been touted as “digital gold”, it is interesting to see the stark difference in trading behaviors between gold and cryptos.

To test whether 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. In contrast, for cryptocurrencies, we find no change in active re-balancing as a function of the return quintile. Thus, in cryptos, investors do not re-balance even after very large price moves and absorb the price changes. For the rest of the paper we focus on cryptocurrencies and stocks, since investors tend to trade gold very similarly to how they trade stocks.

One important question that arises from these results is whether the stark difference in trading patterns is asset specific or a function of investor composition, where some assets attract investors with specific preferences. For example, retail investors with contrarian trading strategies might predominantly invest in stocks and momentum traders in cryptocurrencies. We can rule out this preference based explanation by contrasting investors who trade in both stocks and crypto with those who trade in only one of the two asset classes. Investors who invest in both display the same momentum strategy in cryptocurrencies as those who only trades in crypto, yet, follow 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 an asset specific phenomenon.

We also rule out that certain subgroups with strong preferences for cryptocurrencies drive our results, e.g., younger or financially savvy investors. For individual characteristics we use the self-reported demographic information provided to us by eToro and focus on age, wealth, income, first-traded asset class on the platform, and whether they work in the finance industry. Surprisingly, we do not find strong interactions between ex-ante characteristics and trading strategies. Investors are contrarian in stocks but momentum in cryptocurrencies, independent of their characteristics. This finding is consistent with Giglio et al. (2021) who find that demographic characteristics explain only a small part of why some individuals have optimistic or pessimistic price expectations.

The one group of traders that displays slightly different trading behavior are called “Guru traders". 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. However, 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 second concern could be that our results are explained by investors who do not pay attention to their portfolios continuously. If investors are inattentive, the total portfolio share of an asset can at times increase (decrease) mechanically following positive (negative) returns. Of course, the fact that our results hold even *within* investors, would mean that inattention would have to selectively apply only to cryptocurrencies but not to stocks. This is very unlikely given that the eToro interface shows customers their entire portfolio in an integrated fashion. But to test this hypothesis formally, we focus on times when investors are likely to pay attention to their portfolio. We classify investors as *active* or attentive, if they traded at least once in any asset in the last week, and as *inactive* if they didn't trade at all in the last month. Our results still hold when we focus on the active investors: the dichotomy in stocks and cryptocurrencies remains unchanged, with crypto investments following a momentum strategy and stock investments a contrarian strategy. We do find that inactive investors are more momentum, when it comes to the overall value of their stock portfolios, but less so than for crypto portfolios. 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 the rest of the paper we then ask what might be the rationale why investors adopt de facto momentum strategies in cryptocurrencies. First, since cryptocurrencies have only been around for a short period, investors have not experienced a crash in prices prior to January 2018. As a result they could have naively optimistic beliefs that ultimately these new assets can only go up in value, even if they are volatile in the short run. We see one major crash in cryptocurrency prices at the beginning of 2018. When we split our analysis into time periods before and after the 2018 crash, we observe a slight dampening of the sensitivity of the overall portfolio share of cryptos to returns, but 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 crash, where investors actively rebalance downward after strong price movements. Yet, overall these are very small adjustments which do not change the overall momentum trading in crypto.

Second, investors might trade in lottery-like assets differently than in other types of securities. This would be a preference-based explanation rather than one focused on differential beliefs about cryptocurrencies, as proposed in this paper. However, preference for skewed or lottery-like returns should not be asset specific, and therefore we analyze whether trading in stocks that have lottery-like returns is more similar to trading in cryptocurrencies. We classify stocks into lottery-like returns following the approaches of Bali et al. (2021) and Han et al. (2022). In particular, we use maximum returns in the prior month, volatility of returns, skewness, whether a firm is young, and gross profitability over the past year. We then repeat our main analysis but interact the contemporaneous log returns with measures of the lottery-likeness of firms. We find that investors follow a marginally less contrarian strategy in stocks that are more lottery-like. However, the effect is small and only borderline significant. This suggests that retail investors do not just react to the lottery-like features of cryptocurrency returns.

Third, the difference in trading between cryptos and stocks might be driven by the lack of periodic cashflow information about cryptocurrencies. Luo et al. (2020) suggest that earnings announcement dates provide retail investors with periodic events to reevaluate their beliefs about the valuation of stocks. Retail investors 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 in stocks is especially strong around earnings announcement dates. However, when we split the sample of stock trades into earnings-announcement and non-earnings-announcement dates investors still trade contrarian in stocks even on days without any new cash flow information. Furthermore, the lack of cashflow information cannot be the full explanation behind our findings, since we also find contrarian trading in gold, where similar to cryptocurrencies, investors do not receive cashflow information.

Put together, our results suggest that investors use a different model when forming beliefs about cryptocurrencies compared to stocks. We conjecture that one explanation for the momentum trading behavior among retail investors in cryptocurrencies is that these are a new investment vehicle, whose future value to a large extent depends on investors' beliefs about whether there will be wider market adoption going forward. For example, a lot of institutions and others entities might still be sitting on the sidelines. Thus crypto 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 might look more favorably at cryptocurrencies, these price movements can have an amplification effect. The same logic does not apply to stocks or other traditional asset classes where adoption has already happened.

Our paper relates to a growing literature that analyses the trading behavior of retail investors using account-level data, which started with the pioneering work by Odean (1998) and Barber and Odean

(2000). This early literature highlights the importance of preferences in explaining trading behavior, such as the disposition effect, see for example Barberis and Xiong (2009). This literature is carefully reviewed in Barberis and Thaler (2002) and Curcuru et al. (2010). Preference heterogeneity might also extent to dimensions such as preference for lottery-like stocks, such as in Peng and Xiong (2006), Mitton and Vorkink (2007a) or Kumar (2009). Building on these findings recent work by Balasubramaniam et al. (2021) suggests that this heterogeneity can lead to clientele effects where investors with specific preferences self-select to stocks that align with these preferences. To account for the potential impact of preference based composition effects, our paper focuses on the within-trader differences in behavior across different asset types.

A complementary literature focuses on how retail investors form beliefs about asset returns and the extent these beliefs deviate from rational expectations (see for example Harris and Raviv (1993), Dominitz and Manski (2011), and Adam and Nagel (2022)). A few more recent paper try to tie changes in beliefs more directly to trading behavior. Giglio et al. (2021) use belief changes that are directly elicited from survey responses. Meeuwis et al. (2022) show that risky share rebalancing depends on investors' political views, and thus common information is interpreted through different models of the world. Luo et al. (2020) use a large dataset of trades obtained from a prominent U.S. discount broker. They document that retail investors engage in contrarian trading and that these patterns are especially strong in response to earnings announcements. They propose that 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.

A small but growing literature studies the behavior of retail trading in cryptocurrencies. Benetton and Compiani (2020) couple survey evidence on crypto beliefs with their holdings to estimate a structural model of demand that they match with observed prices. While the paper studies equilibrium responses to policy and risk innovations, their findings confirm our theoretical results that short term optimistic beliefs about prices are associated with larger crypto holdings. Hackethal et al. (2021) and Di Maggio et al. (2022) study the characteristics of investors who self-select to invest in cryptos, using different data sets and locals, thus providing complementary analysis to our paper. And Liu and Tsyvinski (2021) analyze the role of network effects for cryptocurrency returns. Somoza and Didisheim (2022) utilize account-level data of German retail traders to measure the correlation of equity and crypto trades and link it to the increased correlation between these asset classes. While data on retail traders on centralized exchanges only constitute a subset of traders in crypto markets, it can potentially help inform broader dynamics in these markets and thus relate to the work of Carleton Athey et al. (2016), Griffin and Shams (2020), and Makarov and Schoar (2020).

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

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

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:*

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

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

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. As of 2019, the last year of our sample, it had 12M registered users and 1.1M active users, in more than 100 countries.[2] 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 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. [3] 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

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

[3] 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 [4]). 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 parallels 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.

Figure 2 and Table 1 provides summary statistics for the 200,000 traders we observe in our sample. In Figure 2, we report the self-reported residence of the traders in our dataset. Overall we have more than 100 countries. We report the top ten countries, and collapse the rest into "Other" category. As the figure shows, the majority of investors come from European countries (UK, Germany, Italy, etc.), with some coming for Asia (Singapore and Malaysia). The rest of the countries make up less than 1%, each. Table 1 Panel A provides information on account and financial background characteristics of the investors. These traders traded on average 63 times during their average account duration of 1.2 years (or a trade every 7 days, on average). The average user traded 9 different stocks and 2 different cryptocurrencies. The median users traded 2 stocks, which is consistent with other commonly-studied retail datasets (e.g., Hartzmark (2015) and Brav et al. (2022)). The average trade in cryptos is a little under $498 and in stocks $311. 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. Their average account balance at the end of the day is a little under $1,000, which is a significant proportion of their liquid assets.

Panel B reports the daily return 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,

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

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) compared 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 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 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%. This is consistent with findings on correlation of attention versus sentiment across different social media platforms that are frequented by retail investors (Cookson et al. (2022)).

We also obtain data on Robinhood traders from Robintrack.net[5]. We use the data from May 2018, when Robintrack starts until Dec 2019, when our eToro dataset ends. Robintrack provides the unqiue number of Robinhood users holding a given stock on a given day. We focus on the top 200 stocks in the eToro dataset and a semilar measure of unique investors holding a given stock on a given day. We find that the rank correlation between the two datasets is 0.68. This suggests that retail investors on eToro focus on similar stocks as retail investors on Robinhood.

[5] https://robintrack.net/

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 $(SharesOwned_t - SharesOwned_{t-1}) \times \frac{P_{t-1}}{Wealth_{t-1}}$. 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.

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:

$$\begin{aligned}\log(ShareChange_{t,i}) &= \alpha_i + \beta_1 \log(Ret_{t,i}) + \beta_2 \log(CRet1Week_{t,i}) + \beta_3 \log(CRet1Month_{t,i}) \\ &\quad + \beta_4 \log(CRet3Month_{t,i}) + \beta_5 \log(CRet6Month_{t,i}) + \epsilon_{i,t}\end{aligned} \tag{17}$$

Where $i \in Stocks$, $i \in Cryptos$ or gold, with standard errors clustered by date. We include lagged cumulative 1 week, 1 month, 3 month, and 6 month returns as controls. 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. 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. 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 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

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

[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.

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 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 return dates. 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 on 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 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. Since trading in gold behaves very similarly to stocks, in the following analysis we will focus on the dichotomy between stocks and cryptocurrencies only, to reduce the size of the tables we present.

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 subgroups of crypto-currency investors who 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 changes, 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 week (in any asset) while inactive investors are defined as not having traded in any asset in the past month.

Table 7 reports the results. In Panel A, 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 in Panel B we see an interesting difference: Focusing on the total share, 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. To focus even more on investors who are active, we look at investors who traded in any asset today A3. We find that the difference between trading in cryptos and stocks persists, and becomes even more stark. Thus, the momentum trading behavior in cryptos is not due to investors not paying attention.

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 to 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 3 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. We also repeated this analysis for new investors, people who joined eToro in a given month, and we find that the allocation between different securities looks quite similar to Figure 1.

Individual Transactions We also want to confirm that our results are not driven by the cohort level aggregation that we proposed in this paper. Therefore, in Table 9 we repeat our main specification but use individual transaction level data. To avoid the problem of sparse trades and spurious correlations which we discussed before, we include only the top 50% of investors in our sample, based on the number of days investors traded either cryptos or stocks. We focus on investors who traded in both cryptos and stocks during their tenure at eToro. We end up with 58,954 users and slightly over 39 million trades. We rerun our main specification as in Table 3, but now $\log(Total\ Share\ Change_t)$ and $\log(Active\ Share\ Change_t)$ are used at the individual level. We also include individual fixed effects to analyze the changes within a person over time and control for the type of instrument and date. We find similar results to our main specification. This suggests that our results are not distorted by aggregation into cohorts.

Transaction Costs Transaction fees on eToro have been changing over time and across different asset classes. We want to make sure that our results are not driven by cryptocurrencies having higher transaction costs, and therefore investors not rebalancing as often. While we don't have the full history of transaction cost changes for all asset classes, we can see in several ways that differences in transaction fees are not driving the differences in trading between stocks and cryptos. First, if high trading costs, caused investors not to rebalance cryptos as often, we would expect them to rebalance more when returns are higher. Yet, in Table 4 Panel B we see that investors don't actively rebalance their crypto holdings, even in when returns are either very high or very low (top/bottom quintiles). Second, in May/June 2019, eToro removed trading fees for non-levered stock trades in several countries. In Table A5, we examine non-levered trades by active investors (who have traded in the past week), before and after the removal of the fees. In particular, we compare the trading behavior of investors in those countries before May 2019 with their trading after June 2019, and we test whether investors started trading more contrarian after the removal of trading fees. For more details about the removal of trading fees for stocks on eToro see Even-Tov et al. (2022). The results are presented in Table A5. The coefficient on the interaction of returns and the *After Fee* indicator variable is insignificant, suggesting that there was no change in contrarian trading behavior in response to the fee removal. Take together, this evidence suggests that it's unlikely that higher trading fees are the main driver of investors' momentum trading in crytocurrencies.

Individual Assets To ensure that our results are not driven by any individual asset, in Table A6 we replicate our main specification separately for Bitcoin, Ripple, Etherium, and for the top three stocks by dollar amount invested on eToro (Tesla, Amazon, Apple). The results suggest that the momentum trading in cryptocurrencies and the contrarian trading in stocks, are not driven by any given individual asset.

Number of assets Another potential concern is the different number of assets in each asset class. If investors want to be invested in a given asset class, they have only a few cryptos to choose from (on eToro), and thousands of stocks. Therefore, it could be the case, that to be invested in cryptos, it makes the most sense to just buy and hold the asset class, whereas in stocks there are more *perceived* gains from trading between stocks. This behavior could explain the different trading patters we find between cryptos and stocks. We address this alternative explanation in two ways. First, we observe that investors are very contrarian in gold, where there are no other assets that they can trade in and out of. Second, we follow Da et al. (2021) and examine the first trade an investor makes in a given asset class. Not only are these trades more representative of investors' beliefs, they also help us get around the concern that investors just trade out of one stock and into the other, because they think it's a better deal. The results are presented in Table A7. We find that investors enter the crypto asset class, when the returns are positive and enter the stock and gold asset classes when the returns are negative. These findings suggest, that the different number of assets across the asset classes are unlikely to explain our results.

Leverage Some trades on eToro have leverage, and therefore a margin account. We want to ensure that the difference between cryptos and stocks in our data is not driven by differences in propensity to have margin accounts. First, similar to Luo et al. (2020) whose trades don't have leverage, we find that investors are contrarian when it comes to trading in stocks, which provides external validity to the results in our paper. Second, in Table A8, we focus only on trades that don't have leverage, and find similar effects - momentum strategy in cryptocurrencies and contrarian in stocks.

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 a 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 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.

There are a number of alternative channels that could potentially explain our results. The specific candidate explanations we investigate are first, 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, we examine whether investors treat lottery-like assets differently than other types of securities. 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. The beginning of 2018 was the first major crash in cryptocurrencies. 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 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 investors are still following a momentum strategy even after they have seen that prices of cryptocurrencies can go down. [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' strategies don't change much after the crash. Trading in stocks does not show many changes before and after 2018, which should not be surprising since the crash was localized in cryptocurrencies and stock markets were not significantly impacted.

In Appendix Table A9 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 Guru traders, who became even more momentum traders after 2018. However, this change could be a reflection of their own preferences, or of a trading strategy that 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, overall 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 (2007b) 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.

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

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

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. Young firms are defined as firms that are less than a year old. 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 trading. For example, we find that the change in total share as a function of log returns is less negative (and borderline significant) for stocks that had high maximum last-month 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 do not find significant difference for stocks based on their age and profitability. In total, we do not find evidence to suggest that investors are more momentum in all assets with very skewed or volatile returns. Rather this momentum strategy seems to be 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: earnings-announcement days, in columns (1) to (3), compared to non-earnings-announcement days 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 earnings-announcement days 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. To make sure that the difference in trading patterns between earnings-announcement and non-earnings-announcement days is not driven by investor inattention we repeat the analysis in Table A4, but focus only on active investors, defined as having traded any asset in the prior 7 days. We find that the results are similar.

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. 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. On the other hand, there might 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.

References

Adam, K. and Nagel, S. (2022). Expectations data in asset pricing. Working Paper 29977, National Bureau of Economic Research.

Auer, R. and Claessens, S. (2018). Regulating cryptocurrencies: assessing market reactions. *BIS Quarterly Review September*.

Balasubramaniam, V., Campbell, J. Y., Ramadorai, T., and Ranish, B. (2021). Who owns what? a factor model for direct stock holding. Technical report, National Bureau of Economic Research.

Bali, T. G., Hirshleifer, D., Peng, L., and Tang, Y. (2021). Attention, social interaction, and investor attraction to lottery stocks. Technical report, National Bureau of Economic Research.

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

Barberis, N. and Thaler, R. (2002). A survey of behavioral finance. Working Paper 9222, National Bureau of Economic Research.

Barberis, N. and Xiong, W. (2009). What drives the disposition effect? an analysis of a long-standing preference-based explanation. *The Journal of Finance*, 64(2):751–784.

Benetton, M. and Compiani, G. (2020). Investors' beliefs and asset prices: A structural model of cryptocurrency demand. *Available at SSRN 3668582*.

Biais, B., Bisiere, C., Bouvard, M., Casamatta, C., and Menkveld, A. J. (2020). Equilibrium bitcoin pricing. *Available at SSRN 3261063*.

Brav, A., Cain, M., and Zytnick, J. (2022). Retail shareholder participation in the proxy process: Monitoring, engagement, and voting. *Journal of Financial Economics*, 144(2):492–522.

Calvet, L. E., Campbell, J. Y., and Sodini, P. (2009). Measuring the financial sophistication of households. *American Economic Review*, 99(2):393–98.

Campbell, J. Y. and Viceira, L. M. (2002). *Strategic asset allocation: portfolio choice for long-term investors*. Clarendon Lectures in Economic.

Carleton Athey, S., Parashkevov, I., Sarukkai, V., and Xia, J. (2016). Bitcoin pricing, adoption, and usage: Theory and evidence. *Available at SSRN 2826674*.

Cookson, J. A., Lu, R., Mullins, W., and Niessner, M. (2022). The social signal. *Available at SSRN*.

Curcuru, S., Heaton, J., Lucas, D., and Moore, D. (2010). Chapter 6 - heterogeneity and portfolio choice: Theory and evidence. In AÏT-SAHALIA, Y. and HANSEN, L. P., editors, *Handbook of Financial Econometrics: Tools and Techniques*, volume 1 of *Handbooks in Finance*, pages 337–382. North-Holland, San Diego.

Da, Z., Huang, X., and Jin, L. J. (2021). Extrapolative beliefs in the cross-section: What can we learn from the crowds? *Journal of Financial Economics*, 140(1):175–196.

Di Maggio, M., Williams, E., and Balyuk, T. (2022). Cryptocurrency investing: Stimulus checks and inflation expectations. *Available at SSRN 4281330*.

Dominitz, J. and Manski, C. F. (2011). Measuring and interpreting expectations of equity returns. *Journal of applied econometrics*, 26(3):352–370.

Dorn, A. J., Dorn, D., and Sengmueller, P. (2015). Trading as gambling. *Management Science*, 61(10):2376–2393.

Even-Tov, O., George, K., Kogan, S., and So, E. C. (2022). Fee the people: Retail investor behavior and trading commission fees. *Available at SSRN 4226044*.

Gao, X. and Lin, T.-C. (2011). Do individual investors trade stocks as gambling? evidence from repeated natural experiments. *Evidence from Repeated Natural Experiments (August 20, 2011)*.

Giglio, S., Maggiori, M., Stroebel, J., and Utkus, S. (2021). Five facts about beliefs and portfolios. *American Economic Review*, 111(5):1481–1522.

Griffin, J. M. and Shams, A. (2020). Is bitcoin really untethered? *The Journal of Finance*, 75(4):1913–1964.

Hackethal, A., Hanspal, T., Lammer, D. M., and Rink, K. (2021). The Characteristics and Portfolio Behavior of Bitcoin Investors: Evidence from Indirect Cryptocurrency Investments*. *Review of Finance*, 26(4):855–898.

Han, B., Hirshleifer, D., and Walden, J. (2022). Social transmission bias and investor behavior. *Journal of Financial and Quantitative Analysis*, 57(1):390–412.

Harris, M. and Raviv, A. (1993). Differences of Opinion Make a Horse Race. *The Review of Financial Studies*, 6(3):473–506.

Hartzmark, S. M. (2015). The worst, the best, ignoring all the rest: The rank effect and trading behavior. *The Review of Financial Studies*, 28(4):1024–1059.

Kézdi, G. and Willis, R. J. (2011). Household stock market beliefs and learning. Technical report, National Bureau of Economic Research.

Kumar, A. (2009). Who gambles in the stock market? *The Journal of Finance*, 64(4):1889–1933.

Liu, Y. and Tsyvinski, A. (2021). Risks and returns of cryptocurrency. *Review of Financial Studies*, 34(6):2689–2727.

Luo, C., Ravina, E., Sammon, M., and Viceira, L. M. (2020). Retail investors' contrarian behavior around news and the momentum effect. *Available at SSRN 3544949*.

Makarov, I. and Schoar, A. (2020). Trading and arbitrage in cryptocurrency markets. *Journal of Financial Economics*, 135(2):293–319.

Meeuwis, M., Parker, J. A., Schoar, A., and Simester, D. (2022). Belief disagreement and portfolio choice. *The Journal of Finance*, 77(6):3191–3247.

Mitton, T. and Vorkink, K. (2007a). Equilibrium Underdiversification and the Preference for Skewness. *The Review of Financial Studies*, 20(4):1255–1288.

Mitton, T. and Vorkink, K. (2007b). Equilibrium underdiversification and the preference for skewness. *The Review of Financial Studies*, 20(4):1255–1288.

Odean, T. (1998). Are investors reluctant to realize their losses? *The Journal of Finance*, 53(5):1775–1798.

Peng, L. and Xiong, W. (2006). Investor attention, overconfidence and category learning. *Journal of Financial Economics*, 80(3):563–602.

Somoza, L. and Didisheim, A. (2022). The End of the Crypto-Diversification Myth. Swiss Finance Institute Research Paper Series 22-53, Swiss Finance Institute.

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.

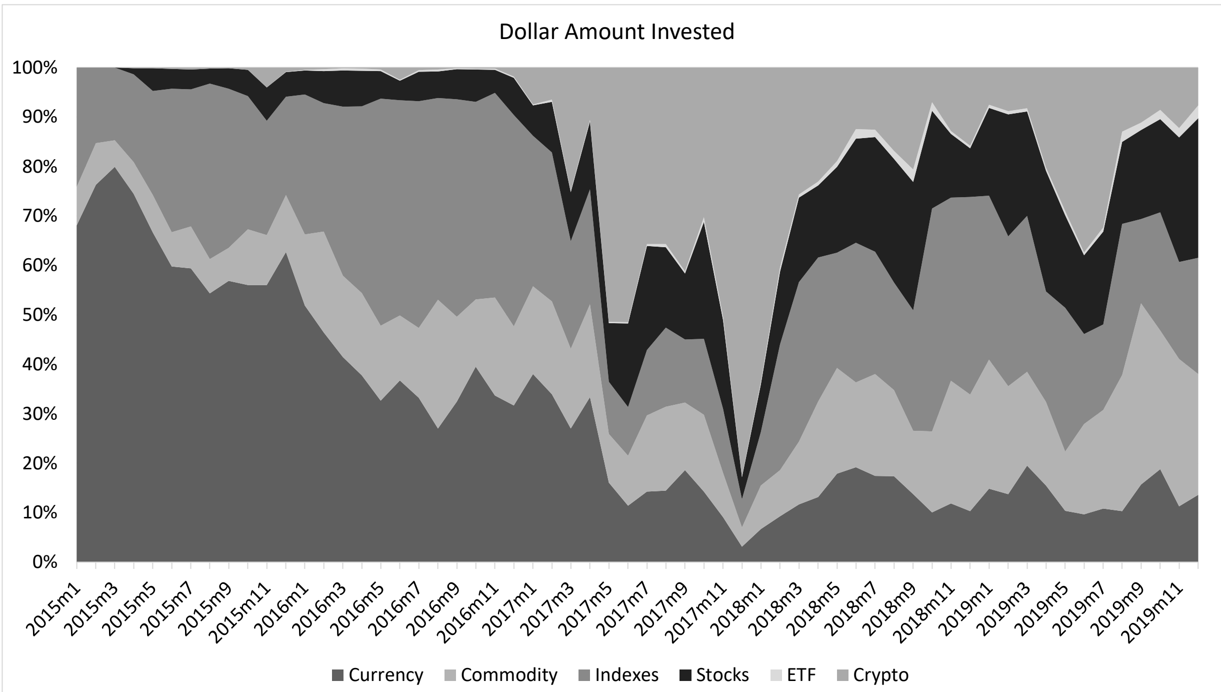

Figure 2. **Investors' Country of Origin**

This figure shows the fraction of investors by self-reported country of origin. We show the top 10 countries and collapse the rest into the "Other" category.

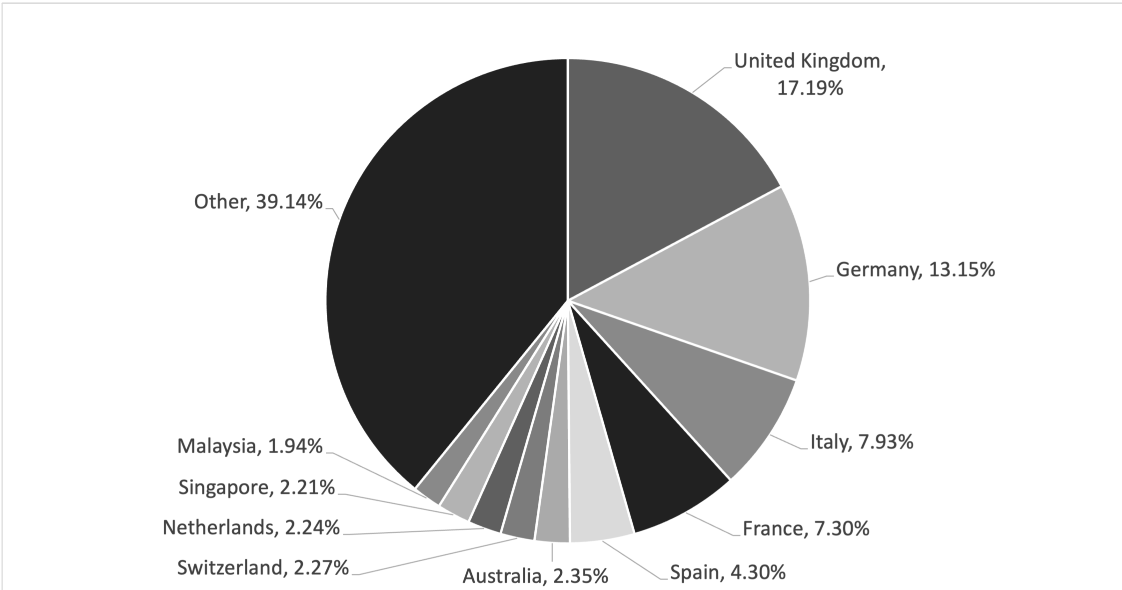

Table 1. **Summary Statistics**

This table displays the summary statistics for our main variables. In Panel A, we display trader characteristics. *Num trades per user* is the number of round-trip trades (opening and closing a position). Holding periods and account age are in days. 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. 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 plus 1. 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	63.21	199.44	1	5	16	52	144	22,304	199,927
Num unique stocks	9.33	21.43	0	0	2	9	25	744	199,927
Num unique cryptos	1.84	1.08	0	1	2	3	3	3	199,927
Account age	489.60	444.19	0	65	366	935	1,054	1,948	199,927
Trade size crypto (\$)	494.48	1628.91	1	100	225	421	945	191,863	172,599
Trade size stocks (\$)	311.30	755.80	1	80	134	285	602	52,234	141,519
Account Balance (\$)	986.99	2042.14	0	60	260	936	2,680	44,837	199,927
Holding period crypto	57.13	119.32	0	3	12	51	155	1,162	167,690
Holding period stocks	23.82	55.72	0	2	7	21	57	1,904	141,182
Finance Background	0.20	0.40	0	0	0	0	1	1	199,927
Low Wealth	0.43	0.49	0	0	0	1	1	1	199,927
Young ($<$ 35yrs age)	0.51	0.50	0	0	1	1	1	1	199,927
Ever Guru	0.01	0.10	0	0	0	0	0	1	199,927

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***			
	(0.01)	(0.01)	(0.01)			
Sentiment				0.008***	0.008***	0.007***
				(0.00)	(0.00)	(0.00)
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 vs. Gold**

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 plus 1, and *Log*(CR past 1 week) is defined as the cumulative return from day $t-7$ to day $t-1$. 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)
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)
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)
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 log cumulative returns for total and active share change regressions, as well as log returns on wealth and net inflows, for active share change. *Cryptos* are BTC, XRP, and ETH. The cutoffs for cryptos are: -0.025, -0.005, 0.007, and 0.029; the cutoffs for stocks are: -0.011, -0.002, 0.004, and 0.012; 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). *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)				
	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
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
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
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
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
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
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(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 log cumulative returns for total and active share change regressions, as well as log 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 log cumulative returns for total and active share change regressions, as well as log 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
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
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
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
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
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 (1)	Ret>0 (2)	Ret≤0 (3)	All (4)	Ret>0 (5)	Ret≤0 (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
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
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
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
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
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*(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 log cumulative returns for total and active share change regressions, as well as log 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
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
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
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
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 log cumulative returns for total and active share change regressions, as well as log 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
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
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 log cumulative returns for total and active share change regressions, as well as log 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 plus 1, and *Log*(CR past 1 week) is defined as the cumulative return from day $t-6$ to day $t-1$. 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 (1)	Ret>0 (2)	Ret≤0 (3)	All (4)	Ret>0 (5)	Ret≤0 (6)
Log(Ret) (z)	0.034***	0.020**	0.043***	-0.015***	-0.049***	0.008
	(0.004)	(0.009)	(0.005)	(0.004)	(0.005)	(0.006)
Log(CR past 1 week) (z)	0.002	0.010**	-0.005	-0.012***	-0.019***	-0.004***
	(0.003)	(0.005)	(0.005)	(0.001)	(0.002)	(0.001)
Log(CR past 1 month) (z)	0.007**	0.005	0.009*	-0.001	-0.003**	0.001
	(0.003)	(0.004)	(0.005)	(0.001)	(0.001)	(0.001)
Log(CR past 3 months) (z)	-0.001	-0.003	0.001	0.002**	0.001	0.004***
	(0.002)	(0.003)	(0.003)	(0.001)	(0.001)	(0.002)
Log(CR past 6 months) (z)	0.002	0.003	-0.003	0.003***	0.002	0.001
	(0.002)	(0.004)	(0.003)	(0.001)	(0.001)	(0.001)
R2	0.002	0.004	0.005	0.001	0.001	0.001
Observations	35,947,357	17,939,954	18,006,622	26,564,195	13,853,351	12,711,703

Panel B

	Log(active share change)					
	Cryptos			Top 200 Stocks		
	All (1)	Ret>0 (2)	Ret≤0 (3)	All (4)	Ret>0 (5)	Ret≤0 (6)
Log(Ret) (z)	-0.016***	-0.028***	-0.009	-0.035***	-0.070***	-0.012**
	(0.004)	(0.009)	(0.005)	(0.004)	(0.005)	(0.006)
Log(CR past 1 week) (z)	0.003	0.010**	-0.005	-0.012***	-0.021***	-0.003***
	(0.003)	(0.005)	(0.005)	(0.001)	(0.002)	(0.001)
Log(CR past 1 month) (z)	0.007**	0.006	0.008*	-0.001	-0.006***	0.002
	(0.003)	(0.004)	(0.005)	(0.001)	(0.001)	(0.001)
Log(CR past 3 months) (z)	-0.001	-0.002	0.001	0.002**	-0.001	0.006***
	(0.002)	(0.003)	(0.003)	(0.001)	(0.001)	(0.002)
Log(CR past 6 months) (z)	0.002	0.003	-0.003	0.003***	0.001	0.003**
	(0.002)	(0.004)	(0.003)	(0.001)	(0.001)	(0.001)
Log(Ret Wealth) (z)	0.049***	0.051***	0.047***	0.030***	0.029***	0.030***
	(0.002)	(0.003)	(0.004)	(0.001)	(0.002)	(0.002)
Log(Ret Net Inflows) (z)	0.059***	0.062***	0.056***	0.034***	0.033***	0.036***
	(0.003)	(0.003)	(0.004)	(0.001)	(0.002)	(0.002)
R2	0.003	0.006	0.006	0.002	0.006	0.005
Observations	35,947,357	17,939,954	18,006,622	26,564,195	13,852,121	12,710,485

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 log cumulative returns for total and active share change regressions, as well as log 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)	0.054***	0.059***	0.049***	-0.015***	-0.037***	-0.009
	(0.003)	(0.005)	(0.007)	(0.004)	(0.009)	(0.007)
After Crash	-0.011**	-0.007	-0.025***	-0.016***	-0.020***	-0.031***
	(0.005)	(0.007)	(0.008)	(0.004)	(0.007)	(0.007)
After Crash × Log(Ret) (z)	-0.001	0.001	-0.009	-0.002	0.014	-0.019*
	(0.003)	(0.006)	(0.007)	(0.006)	(0.011)	(0.010)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
R2	0.245	0.197	0.138	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)
Log(Ret) (z)	-0.000	0.005	-0.007	-0.041***	-0.063***	-0.035***
	(0.003)	(0.005)	(0.006)	(0.004)	(0.009)	(0.007)
After Crash	-0.009*	-0.006	-0.020**	-0.014***	-0.017***	-0.030***
	(0.005)	(0.007)	(0.008)	(0.004)	(0.007)	(0.007)
After Crash × Log(Ret) (z)	-0.000	0.002	-0.006	-0.003	0.012	-0.020**
	(0.003)	(0.005)	(0.007)	(0.006)	(0.011)	(0.010)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
R2	0.018	0.020	0.036	0.008	0.007	0.009
Observations	3,553	1,847	1,706	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 log cumulative returns for total and active share change regressions, as well as log 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)
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)
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)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
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)
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)
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)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
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)
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)
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)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
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)
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)
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)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
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)
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)
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)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
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 log cumulative returns for total and active share change regressions, as well as log 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
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
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. **Cryto and Gold traders: Cryptos vs. Stocks vs. Gold**

In this table we examine how contemporaneous and lagged returns affect individuals' trading behavior. We focus on investors who have traded both cryptos and gold during their tenur. 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 plus 1, and Log(CR past 1 week) is defined as the cumulative return from day $t-7$ to day $t-1$. 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)	0.036***	0.039***	0.032***	-0.002	-0.000	-0.005**
	(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	0.003	-0.001	0.001	0.001	0.000
	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Log(CR past 3 months) (z)	-0.005**	-0.004*	-0.007**	-0.005***	-0.004*	-0.007**
	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)
Log(CR past 6 months) (z)	0.005**	0.002	0.008**	0.005**	0.001	0.008**
	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)
Log(Ret Wealth) (z)				0.002	0.002	0.004
				(0.001)	(0.002)	(0.002)
Log(Ret Net Inflows) (z)				0.006***	0.006**	0.005**
				(0.002)	(0.003)	(0.002)
R2	0.277	0.310	0.245	0.018	0.018	0.030
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)	-0.010***	-0.011***	-0.011***	-0.030***	-0.029***	-0.032***
	(0.002)	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)
Log(CR past 1 week) (z)	-0.002	-0.004*	-0.001	-0.002*	-0.004**	-0.001
	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)
Log(CR past 1 month) (z)	-0.003*	-0.003	-0.002	-0.003*	-0.003	-0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Log(CR past 3 months) (z)	0.002	0.001	0.003	0.002	0.001	0.003
	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)	(0.002)
Log(CR past 6 months) (z)	0.001	0.001	0.002	0.002	0.001	0.002
	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)
Log(Ret Wealth) (z)				0.009***	0.006***	0.012***
				(0.002)	(0.002)	(0.003)
Log(Ret Net Inflows) (z)				0.001	0.002	-0.001
				(0.001)	(0.002)	(0.002)
R2	0.001	0.001	0.001	0.008	0.005	0.011
Observations	168,446	86,615	81,831	168,446	86,615	81,831

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)	-0.189***	-0.185***	-0.181***	-0.193***	-0.189***	-0.190***
	(0.019)	(0.023)	(0.025)	(0.019)	(0.022)	(0.026)
Log(CR past 1 week) (z)	0.029*	0.020	0.037*	0.029*	0.021	0.034
	(0.015)	(0.019)	(0.022)	(0.015)	(0.019)	(0.022)
Log(CR past 1 month) (z)	0.006	0.022	-0.027	0.006	0.019	-0.024
	(0.023)	(0.034)	(0.033)	(0.023)	(0.033)	(0.034)
Log(CR past 3 months) (z)	0.009	-0.045*	0.072**	0.009	-0.045*	0.070**
	(0.021)	(0.026)	(0.033)	(0.021)	(0.026)	(0.033)
Log(CR past 6 months) (z)	0.006	-0.023	0.036*	0.005	-0.022	0.035
	(0.016)	(0.025)	(0.022)	(0.017)	(0.025)	(0.021)
Log(Ret Wealth) (z)				0.008	0.002	0.012
				(0.014)	(0.017)	(0.022)
Log(Ret Net Inflows) (z)				-0.003	0.011	-0.017
				(0.015)	(0.021)	(0.020)
R2	0.168	0.175	0.208	0.173	0.180	0.217
Observations	1,150	586	564	1,150	586	564

Table A3. **Active Investors who Traded Today**

In this table we examine whether investors trade similarly when we define active as 'traded today'. 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 been on eToro for at least 30 days, and have traded both cryptos and stocks during their tenure there. 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 log cumulative returns for total and active share change regressions, as well as log 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.

	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)	0.025***	0.041***	0.006	-0.029**	-0.030***	-0.052***
	(0.005)	(0.008)	(0.013)	(0.004)	(0.008)	(0.008)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Outcome SD	0.370	0.364	0.375	1.344	1.348	1.340
R2	0.005	0.013	0.002	0.000	0.000	0.000
Observations	3,468	1,790	1,678	165,100	84,946	80,154

	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)	-0.007& 0.007	-0.008	-0.036***	-0.056***	-0.024***	
	(0.006)	(0.007)	(0.013)	(0.004)	(0.008)	(0.006)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Outcome SD	0.741	0.722	0.759	1.348	1.353	1.343
R2	0.810	0.816	0.806	0.007	0.007	0.006
Observations	3,468	1,790	1,678	165,100	84,946	80,154

Table A4. **Stock Trading around Earnings Announcements – Active Investors**

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, and were active on day t, which is defined as having traded any asset in the prior 7 days. *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 log cumulative returns for total and active share change regressions, as well as log 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)	-0.039***	-0.070***	-0.043***	-0.009***	-0.016***	-0.008
	(0.006)	(0.011)	(0.011)	(0.003)	(0.005)	(0.005)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
R2	0.009	0.013	0.010	0.000	0.001	0.000
Observations	23,490	11,772	11,718	143,435	74,088	69,347

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)	-0.066***	-0.096***	-0.070***	-0.033***	-0.042***	-0.033***
	(0.006)	(0.011)	(0.011)	(0.003)	(0.005)	(0.005)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
R2	0.027	0.026	0.029	0.005	0.004	0.005
Observations	23,490	11,772	11,718	143,435	74,088	69,347

Table A5. **Fee Removals**

In this table we examine whether the removal of trading fees in various countries has changed the way individuals trade in stocks. We generate a representative investor, by cumulating trades, net inflows, and wealth, across investors who participated on the platform at date t. We focus on investors who were active (traded on eToro in the past week), and traded in both stocks and cryptos during their tenure at eToro. We also focus on no-leverage trades, since they were the ones affected by the trading fee removals. The fees in our sample were removed in May and June of 2019 (depending on the country). We exclude those two months from our analysis and compare the 'before period', before May 2019 to the "After Fee" period, which is after June 2019. For more details about the fee removal see Even-Tov et al. (2022) $Log(\text{Total Share Change}_t)$ is defined as $\log(\text{Active Share Change}_t) + \log(Price_t/Price_{t-1}) - Log(Wealth_t/Wealth_{t-1})$. $Log(\text{Active Share Change}_t)$ defined as $\log(\text{Shares owned}_t) - \log(\text{Shares owned}_{t-1})$. Controls include lagged 1 week, 1 moth, 3 month, and 6 month log cumulative returns for total and active share change regressions, as well as log returns on wealth and net inflows, for active share change, as well as their interactions with the *After Fee* indicator variable. 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).. Statistical significance is denoted at the ten, five, and one percent levels by *, **, and ***, respectively.

	Top 200 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)	0.000	-0.004	-0.008***	-0.019***	-0.025***	-0.028***
	(0.002)	(0.004)	(0.003)	(0.002)	(0.004)	(0.003)
After Fee	0.002	-0.000	-0.004	-0.005	-0.010	-0.012
	(0.003)	(0.005)	(0.005)	(0.005)	(0.008)	(0.008)
After Fee × Log(Ret) (z)	0.001	0.006	-0.005	-0.001	0.006	-0.007
	(0.003)	(0.006)	(0.006)	(0.003)	(0.006)	(0.006)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
R2	0.000	0.001	0.001	0.004	0.003	0.006
Observations	154,109	79,547	74,562	154,109	79,547	74,562

Table A6. **Individual Assets**

In this table we examine how contemporaneous and lagged returns affect individuals' trading behavior in each asset, rather than looking at the assets together in one regression. 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 plus 1, and Log(CR past 1 week) is defined as the cumulative return from day $t-7$ to day $t-1$. 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 and focuse on BTC, XRP, and ETH. In Panel B we examine stocks, and focus on Tesla, Amazon, and Appple. 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)		
	BTC (1)	ETH (2)	XRP (3)	BTC (4)	ETH (5)	XRP (6)
Log(Ret) (z)	0.041***	0.037***	0.030***	-0.004*	0.007*	-0.005
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)
Log(CR past 1 week) (z)	-0.000	0.004**	0.003	-0.000	0.003***	0.003*
	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)
Log(CR past 1 month) (z)	-0.000	0.001	-0.002	0.000	-0.000	-0.002*
	(0.003)	(0.001)	(0.001)	(0.003)	(0.001)	(0.001)
Log(CR past 3 months) (z)	0.002	0.004***	-0.008***	0.003	0.004***	-0.009***
	(0.003)	(0.002)	(0.002)	(0.003)	(0.001)	(0.002)
Log(CR past 6 months) (z)	-0.006**	-0.005***	0.016***	-0.009***	-0.005***	0.014***
	(0.003)	(0.001)	(0.004)	(0.003)	(0.001)	(0.004)
Log(Ret Wealth) (z)				0.003**	-0.005	0.004
				(0.001)	(0.003)	(0.003)
Log(Ret Net Inflows) (z)				0.007***	0.002	0.009***
				(0.003)	(0.002)	(0.002)
R2	0.220	0.530	0.436	0.015	0.072	0.159
Observations	1,708	1,020	858	1,708	1,020	858

Panel B: Stocks

	Log(total share change)			Log(active share change)		
	Tesla (1)	Amazon (2)	Apple (3)	Tesla (4)	Amazon (5)	Apple (6)
Log(Ret) (z)	0.000	0.007	-0.003	-0.020***	-0.010***	-0.020***
	(0.004)	(0.008)	(0.005)	(0.004)	(0.003)	(0.005)
Log(CR past 1 week) (z)	-0.006**	0.007*	-0.005	-0.006***	0.005	-0.007*
	(0.002)	(0.004)	(0.004)	(0.002)	(0.004)	(0.003)
Log(CR past 1 month) (z)	0.002	0.003	-0.001	0.002	0.002	-0.000
	(0.002)	(0.006)	(0.003)	(0.002)	(0.005)	(0.003)
Log(CR past 3 months) (z)	0.001	-0.000	0.002	-0.001	0.002	0.002
	(0.003)	(0.006)	(0.003)	(0.003)	(0.006)	(0.003)
Log(CR past 6 months) (z)	-0.001	0.005	0.002	0.002	0.004	0.004
	(0.003)	(0.004)	(0.004)	(0.003)	(0.004)	(0.003)
Log(Ret Wealth) (z)				0.002	0.004*	0.005**
				(0.002)	(0.002)	(0.002)
Log(Ret Net Inflows) (z)				-0.002	0.001	0.000
				(0.002)	(0.003)	(0.004)
R2	0.006	0.013	0.003	0.099	0.018	0.038
Observations	1,173	1,173	1,173	1,173	1,173	1,173

Table A7. **First trade in an Asset Class: Cryptos vs. Stocks vs. Gold**

In this table we examine how contemporaneous and lagged returns affect individuals' first trade in a given asset class. We generate a representative investor, by cumulating trades, net inflows, and wealth, across all investors who made their first trade in the given asset class 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 plus 1, and Log(CR past 1 week) is defined as the cumulative return from day $t-7$ to day $t-1$. 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. In Panel B, we also control for the NASDAQ composite index contemporaneous and past cumulateive returns. *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)	0.110***	0.210***	-0.003	0.060***	0.114***	0.015
	(0.022)	(0.025)	(0.040)	(0.021)	(0.029)	(0.041)
Log(CR past 1 week) (z)	-0.038	-0.005	-0.070**	-0.048**	-0.012	-0.079**
	(0.024)	(0.033)	(0.031)	(0.024)	(0.032)	(0.031)
Log(CR past 1 month) (z)	-0.005	0.012	-0.021	-0.018	0.006	-0.033
	(0.025)	(0.033)	(0.035)	(0.025)	(0.034)	(0.034)
Log(CR past 3 months) (z)	0.014	-0.009	0.012	0.001	-0.017	-0.005
	(0.028)	(0.034)	(0.042)	(0.027)	(0.034)	(0.041)
Log(CR past 6 months) (z)	-0.013	-0.058*	0.014	-0.036	-0.071**	-0.014
	(0.026)	(0.033)	(0.037)	(0.026)	(0.033)	(0.036)
Log(Ret Wealth) (z)				0.017	0.093***	-0.060
				(0.029)	(0.033)	(0.040)
Log(Ret Net Inflows) (z)				0.112***	0.095***	0.128***
				(0.023)	(0.028)	(0.035)
R2	0.010	0.040	0.004	0.012	0.034	0.016
Observations	3,228	1,668	1,560	3,228	1,668	1,560

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)	-0.034***	0.008	-0.098**	-0.028***	0.007	-0.131***
	(0.018)	(0.009)	(0.039)	(0.018)	(0.009)	(0.039)
Log(CR past 1 week) (z)	0.001	0.038	-0.033	0.002	0.038	-0.032
	(0.019)	(0.026)	(0.026)	(0.019)	(0.026)	(0.026)
Log(CR past 1 month) (z)	0.006	-0.045	0.058*	0.005	-0.046	0.057
	(0.024)	(0.031)	(0.035)	(0.024)	(0.031)	(0.035)
Log(CR past 3 months) (z)	-0.016	0.034	-0.049	-0.016	0.035	-0.049
	(0.037)	(0.053)	(0.051)	(0.037)	(0.053)	(0.051)
Log(CR past 6 months) (z)	0.020	0.042	0.030	0.019	0.040	0.030
	(0.031)	(0.046)	(0.046)	(0.031)	(0.046)	(0.046)
Log(NASDAQ Ret)	-0.285	-0.226	-0.533	0.173	0.352	0.060
	(1.901)	(2.581)	(2.601)	(1.978)	(2.588)	(2.723)
Log(NASDAQ CR past 1 week)	0.593	1.073	0.350	0.546	1.078	0.301
	(0.837)	(0.962)	(1.280)	(0.837)	(0.968)	(1.276)
Log(NASDAQ CR past 1 month)	-0.076	0.419	-0.256	-0.084	0.418	-0.272
	(0.470)	(0.596)	(0.662)	(0.469)	(0.595)	(0.662)
Log(NASDAQ CR past 3 months)	-0.178	-0.117	-0.519	-0.166	-0.111	-0.513
	(0.392)	(0.404)	(0.596)	(0.392)	(0.404)	(0.597)
Log(NASDAQ CR past 6 months)	-0.086	-0.294	-0.537	-0.068	-0.294	-0.526
	(0.224)	(0.256)	(0.344)	(0.225)	(0.258)	(0.343)
Log(Ret Wealth) (z)				0.021	0.024	0.015
				(0.025)	(0.034)	(0.026)
Log(Ret Net Inflows) (z)				0.011	0.024	0.010
				(0.018)	(0.022)	(0.024)
NASDAQ Ret Controls	Yes	Yes	Yes	Yes	Yes	Yes
R2	0.000	0.004	0.006	0.001	0.003	0.008
Observations	17,232	9,235	7,997	17,232	9,235	7,997

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)	-0.009	0.133	-0.187***	-0.012	0.115	-0.196***
	(0.059)	(0.086)	(0.064)	(0.058)	(0.080)	(0.064)
Log(CR past 1 week) (z)	0.013	0.055	-0.025	0.014	0.043	-0.029
	(0.054)	(0.075)	(0.076)	(0.053)	(0.076)	(0.077)
Log(CR past 1 month) (z)	-0.012	0.017	-0.062	-0.019	0.013	-0.057
	(0.056)	(0.076)	(0.085)	(0.057)	(0.077)	(0.087)
Log(CR past 3 months) (z)	0.029	-0.037	0.072	0.033	-0.027	0.070
	(0.068)	(0.090)	(0.102)	(0.068)	(0.089)	(0.103)
Log(CR past 6 months) (z)	-0.001	0.090	-0.089	0.003	0.099	-0.091
	(0.058)	(0.082)	(0.079)	(0.058)	(0.082)	(0.079)
Log(Ret Wealth) (z)				-0.032	-0.056	-0.000
				(0.041)	(0.059)	(0.056)
Log(Ret Net Inflows) (z)				0.071	0.163***	-0.029
				(0.047)	(0.062)	(0.061)
R2	0.000	0.015	0.021	0.004	0.029	0.023
Observations	1,095	558	537	1,095	558	537

Table A8. **Overall and Active Share Change: No leverage**

In this table we examine how contemporaneous and lagged returns affect individuals' trading behavior for trades with no leverage. 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 plus 1, and Log(CR past 1 week) is defined as the cumulative return from day $t-7$ to day $t-1$. 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, and in Panel B stocks. *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***	0.040***	0.029***	-0.001	0.003	-0.007***
	(0.001)	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)
Log(CR past 1 week) (z)	0.003**	0.006***	0.000	0.003**	0.005**	0.001
	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)
Log(CR past 1 month) (z)	0.001	0.003	-0.001	0.000	0.000	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	-0.001	0.005**
				(0.001)	(0.002)	(0.002)
Log(Ret Net Inflows) (z)				0.007***	0.007**	0.006***
				(0.002)	(0.003)	(0.002)
R2	0.299	0.355	0.242	0.029	0.040	0.040
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)	0.004***	0.008***	0.001	-0.017***	-0.011***	-0.021***
	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)
Log(CR past 1 week) (z)	-0.006***	-0.007***	-0.006***	-0.006***	-0.007***	-0.005***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Log(CR past 1 month) (z)	-0.001	-0.001	-0.001	-0.002*	-0.001	-0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Log(CR past 3 months) (z)	0.000	-0.000	0.000	-0.000	-0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Log(CR past 6 months) (z)	0.001	0.003*	-0.000	0.001	0.004**	-0.000
	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Log(Ret Wealth) (z)				0.004***	0.003**	0.005***
				(0.001)	(0.001)	(0.001)
Log(Ret Net Inflows) (z)				0.001	-0.001	0.002*
				(0.001)	(0.001)	(0.001)
R2	0.002	0.003	0.001	0.009	0.004	0.016
Observations	169,151	87,050	82,101	169,151	87,050	82,101

Table A9. **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 log cumulative returns for total and active share change regressions, as well as log 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 (1)	Ret>0 (2)	Ret≤0 (3)	All (4)	Ret>0 (5)	Ret≤0 (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
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
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
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
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
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
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
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
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
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
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