Are Cryptos Different? Evidence from Retail Trading*

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Abstract

Trading in cryptocurrencies grew rapidly over the last decade, dominated by retail investors. Using data from eToro, we show that retail traders are contrarian in stocks and gold, yet the same traders follow a momentum-like strategy in cryptocurrencies. The differences are not explained by individual characteristics, investor composition, inattention, differences in fees, or preference for lottery-like assets. We conjecture that retail investors have a model where cryptocurrency price changes affect the likelihood of future widespread adoption, which leads them to further update their price expectations in the same direction.

Keywords: Cryptocurrencies, FinTech, Retail trading, Social finance

JEL Codes: G41, G12, G14

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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.” Unlike traditional markets, trading in cryptocurrencies has been dominated by retail investors. While a large and vibrant literature has looked at retail trading in traditional asset classes, little evidence exists on how investors trade in these new assets. Given the novelty of cryptocurrency markets, investors might have developed different valuation models for cryptocurrencies compared to traditional assets, which shape how they form price expectations in cryptocurrencies. At the same time, cryptocurrencies might have also attracted new types of investors, and thus any differences between cryptocurrencies and other assets could be a function of the composition of investors who participate in these markets.

To study the trading behavior of retail investors in cryptocurrencies and more traditional asset classes, 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 setup allows us to analyze differences in trading behavior across assets, holding constant individual preferences and circumstances.

We show a stark dichotomy between investors’ trading strategies in cryptocurrencies and those in stocks and commodities. Retail investors trade contrarian in stocks and gold, yet they hold on to their cryptocurrency investments even after large price movements, which results in investors following a momentum-like strategy in cryptocurrencies.[1] Importantly, these results hold even when we focus on the same investors trading in different asset classes. We show that individual characteristics do not explain the differences in how investors trade in cryptocurrencies compared to stocks, suggesting that our results are not driven by differences in investor composition or clientele effects. We also show that our results are not the outcome of inattention, differential preferences for lottery-like assets, differences in fees, or the lack of cash flow information about cryptocurrencies. We conjecture that retail investors have a model of cryptocurrency prices in which positive returns increase the likelihood of future widespread adoption, which in turn leads them to update their price expectations in the direction of the price change, consistent with Cong et al. (2020) or Sockin and Xiong (2023). These dynamics are absent in traditional assets, where wider adoption has already happened.

In our empirical analysis, we use the 200 most traded stocks on eToro, which account for over 91%

[1] This crypto trading strategy is often referred to as HODLING among crypto investors on social media, since an early investor mis-spelled “holding on” as “hodling on.”

of stock trading on the platform during our sample period. Similarly, we focus on the three most traded cryptocurrencies—Bitcoin, Ethereum, and Ripple—which constitute over 78% of cryptocurrency trading during the sample period.

We start our analysis by regressing the logarithm of the day-to-day change in the *total portfolio share* of a given asset on both contemporaneous and lagged returns. A prominent aspect of retail investor trading is that many people only trade sporadically, entering or exiting the market for reasons unrelated to their investment beliefs—perhaps due to distractions or inattentiveness. To minimize the impact of measurement noise, we aggregate the portfolio share at the cohort level. This method is conceptually similar to the practice of sorting individual stocks into characteristics portfolios in asset pricing tests, which is commonly used to reduce the effect of idiosyncratic noise on parameter estimates. Since cohorts can be defined based on various characteristics such as age, income, gender, and others, analyzing data at the cohort level allows us to retain meaningful variations and explore heterogeneity in individual trading behavior. We corroborate the robustness of our findings by replicating our main tests at the individual account level.

We find that for stocks, there is a significant negative relationship between the change in the total portfolio share allocated to a given stock and its contemporaneous return. Lagged cumulative returns one week out have still a negative, but a much weaker, relationship to portfolio share changes, and returns do not have a significant impact beyond one week. In contrast, when we repeat the same analysis for cryptocurrencies, we find a strong *positive* relationship between the changes in the total share allocated to cryptocurrencies and the contemporaneous returns. We also find a much weaker, but still positive, relationship for cumulative lagged returns one week out. Thus, our results imply that returns have a strong, persistent effect on total portfolio shares and that investors are contrarian in stocks but exhibit momentum-like behavior in cryptocurrencies. We also repeat this analysis for commodities, focusing specifically on gold, which often draws parallels to Bitcoin as "digital gold" and is the most traded commodity on eToro after oil.[2] We find that, unlike in cryptocurrencies, investments in gold exhibit contrarian dynamics.

The trading strategy for cryptocurrencies is not explained by differences in statistical return properties across these asset classes. Similar to stocks, cryptocurrencies do not display meaningful autocorrelation at the daily level.[3] While there is some evidence for autocorrelation of crypto returns at the weekly or monthly levels during our sample period (Liu and Tsyvinski (2021)), these time horizons are

[2]The pricing of oil is more challenging to measure because there are multiple potential prices to which investors might react; consequently, it is not as amenable to the type of analysis we conduct here.

[3]During our period, a standard deviation increase in day t's returns is associated with a -0.2% change in day $t+1$ crypto returns, a -0.04% change in day $t+1$ stock returns, and a 0.007% change in day $t+1$ gold returns. These result are not statistically significant even at a 10% level.

not relevant for most investors in our data who hold their positions for shorter time periods. We can also rule out that the results are the outcome of reverse causality, i.e., investor trading driving prices. The investors in our sample, in aggregate, own a small fraction of the overall capital traded in the crypto markets, and are therefore price takers.

Following Calvet et al. (2009) we break out the change in the total portfolio share into passive and active shares. Active share constitutes the part of the change in the total share that is due to investors actively rebalancing their portfolio allocation. The remainder is 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's total share of the portfolio will increase over time. For an attentive investor the important statistic is the 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 be perfectly attentive to price changes, it is informative to analyze how active re-balancing interacts with passive changes in the portfolio.

We find that the contrarian trading behavior in the total share changes that we observe for stocks and gold is due to investors actively reducing (increasing) their portfolio holdings in stocks that have high (low) 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-like behavior in the total share of the portfolio is predominantly driven by investors not re-balancing their holdings in cryptocurrencies, whether the price goes up or down. Thus, these investors absorb price swings without adjusting their portfolios. In fact, we show that even for days that have extreme return swings in cryptocurrencies, investors do not rebalance their shares in cryptocurrencies.[4]

A question that arises from these results is whether the stark differences in trading patterns are asset class-specific or a function of investor composition. For example, retail investors with contrarian trading strategies might be predominantly attracted to stocks and momentum traders to cryptocurrencies. By looking at investors who trade in both stocks and cryptos we are able to rule out a clientele-based explanation. Retail investors who trade in both asset classes display the same momentum-like strategy in cryptocurrencies as those who only trade in cryptos. Similarly, these investors also 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 stocks and cryptos. In short, we confirm that the dichotomy in trading behavior holds even *within* a given investor and thus is an asset-specific

[4]For the rest of the paper we focus on cryptocurrencies and stocks, since investors tend to have a contrarian strategy in both gold and stocks.

phenomenon. We also show that the dichotomy between crypto and stock trading holds across different demographic groups, even those that are often believed to have strong preferences for cryptocurrencies, e.g., younger or financially savvy investors.[5] Investors are contrarian in stocks but momentum-like 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.

A second question about the results is whether they could be explained by investors not paying attention to their portfolios. The fact that our results hold even *within* investors, rules out a simple story of cross-sectional differences in attention between asset classes, since these investors actively re-balance their stock portfolios. Instead, inattention would have to selectively apply only to cryptocurrencies, which is unlikely given that the eToro interface shows customers their entire portfolio in an integrated fashion each time they look at it. However, to test more formally if inattention drives the difference in investment strategies, we identify times when investors are paying attention to their portfolios. 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 active investors: the dichotomy in stocks and cryptocurrencies remains unchanged, with crypto investments following a momentum-like strategy and stock investments a contrarian strategy. For inactive investors we find that they are more momentum, when it comes to the overall value of their stock and crypto portfolios. These results suggest that the measured changes in total portfolio shares are an expression of investor updating their price expectations and not just passively riding out price movements.[6] We further ensure that our results are not driven by investors who only 'dabble' in cryptos: we find similar results for active investors who have at least 30% of their portfolio allocated to cryptos and at least 30% allocated to stocks, suggesting that investors display this dichotomy in trading behavior even when a large part of their portfolio is at stake.

In the second part of the paper we examine a possible rationale for why investors adopt a momentum-like strategy in cryptocurrencies. First, since cryptocurrencies have only been around for a short period of time, investors had not experienced a real crypto crash prior to January 2018. As a result they could have held naively optimistic beliefs that ultimately these new assets can only go up in value in the long run, even if they are volatile in the very short run. We observe one major crash in cryptocurrency prices during our sample period - at the beginning of 2018 - where the price of Bitcoin more than halved over a

[5] We use self-reported demographic information which people fill out when opening an account and which are provided to us by eToro, in particular age, wealth, gender, guru status, and whether they work in the finance industry.

[6] The goal of this analysis is to rule out that inattention is driving our results. While interesting in its own right, we are not trying to test the nature of inattention in this paper. We discuss in Section 4 different models of inattention that the literature has considered.

four-month period. When we compare investors' trading behavior before and after the 2018 crash, there is no change either in investors' active rebalancing strategy, or in the total share change. Therefore, even after observing a large price drop investors did not change their momentum-like trading strategy in cryptocurrencies.

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, preferences 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 by whether they have lottery-like returns following the approaches of Bali et al. (2021) and Han et al. (2022). In particular, the following factors are used for classification: maximum returns, volatility of returns, and skewness of returns over the prior month, as well as whether a firm is young, and the gross profitability over the last calendar year. We then repeat our main analysis, but interact the contemporaneous log returns with measures of 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. Thus, retail investors' trading behavior is not solely explained by their reaction 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 stock's value. Retail investors trade contrarian around those dates, since they seem to believe that other investors are overly optimistic or pessimistic about prices. 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 periods we find that investors still trade contrarian in stocks even on days without any major cash flow news. Furthermore, the lack of cashflow information cannot fully explain our findings, since we also find contrarian trading in gold, where similar to cryptocurrencies, investors do not receive cashflow information.

Finally, since cryptocurrencies tend to have higher trading fees than stocks, investors might hold their crypto positions longer, until the returns to trading outweigh the higher fees. We address this possibility in two ways. First, historically, fees for trading gold have also been high relative to fees for stocks, yet retail investors trade contrarian in gold. Second, in April and May 2019, eToro removed fees for trading stocks in 18 countries (for details see Even-Tov et al. (2022)). If higher fees were causing investors to rebalance their portfolios less often, we would expect an increased rebalancing of their stock positions after the fee removal. However, when we compare the trading behavior in stocks in those countries before and after the change, we do not find an increase in rebalancing. This suggests that differences in fees are unlikely to be driving the lower rates of rebalancing in cryptocurrencies.

These tests suggest that investors use a different model when forming beliefs about cryptocurrencies compared to stocks. We conjecture that one explanation for the momentum-like 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, institutions and other entities might still be sitting on the sidelines (Dong et al. (2023)). Thus crypto investors might use price movements as an indicator of changes in the probability 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 a long time ago.

There are several reasons why retail investors might have different models of price formation for cryptocurrencies than for stocks. For stocks, recent empirical papers suggest that retail investors display contrarian trading strategies, especially around earnings announcements (e.g., Kaniel et al. (2008), Grinblatt and Keloharju (2000), and Luo et al. (2020)). Theoretically, there are several behavioral biases that could explain these trading patterns in stocks. On the one hand, retail investors might be overconfident about their ability to interpret stock market data, believing that other investors overreact to information (e.g., Daniel et al. (1998), Scheinkman and Xiong (2003), Hong et al. (2006) and more recently Bastianello and Fontanier (2022)). On the other hand, retail investors might switch between mean reverting and momentum strategies depending on what they perceive as the representativeness or salience of past returns (e.g., Barberis et al. (1998)).

In contrast, cryptocurrency investors do not get regular cash flow updates and thus might not have many opportunities to believe that others are overreacting to disclosed information. Instead their overconfidence might lead them to believe that they are faster than others to understand this new technology and thus expect prices to keep going up. This bears similarity to the models of naive herding (e.g., Eyster and Rabin (2010) and Greenwood and Hanson (2014)). However, even rational investors might adopt a momentum-like strategy in cryptocurrency trading, as long as they believe that there are positive network externalities in cryptos so that higher prices lead to more adoption which in turn creates further growth. A few recent papers provide models of this positive feedback loop (e.g., Cong et al. (2020), and Sockin and Xiong (2023)). In a similar vein, Liu and Tsyvinski (2021) and Borri et al. (2022) provide suggestive evidence that returns predict future growth in cryptocurrency adoption.

2. Related Literature

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 (e.g., Barberis and Xiong (2009)). This literature is carefully reviewed in Barberis and Thaler (2002) and Curcuru et al. (2010). Preference heterogeneity might also extend to dimensions such as preference for lottery-like stocks (e.g., Peng and Xiong (2006), Mitton and Vorkink (2007a), and 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 into 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 to which these beliefs deviate from rational expectations (e.g., Harris and Raviv (1993), Dominitz and Manski (2011), and Adam and Nagel (2022)). Several recent papers 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 in stocks and that these patterns are especially strong in response to earnings announcements.

A small but growing literature studies the behavior of retail trading in cryptocurrencies. Benetton and Compiani (2020) couple survey evidence on crypto beliefs with investors' holdings to estimate a structural model of demand that the authors match with observed prices. While the paper studies equilibrium responses to policy and risk innovations, their findings corroborate our results that short-term optimistic beliefs about prices are associated with larger crypto holdings. Hackethal et al. (2021), Pursiainen and Toczynski (2022), and Di Maggio et al. (2022) study the characteristics of investors who self-select into investing in cryptos. This analysis is complementary to ours since we are looking at within-person differences when trading in different assets. Hackethal et al. (2021) analyze data from a German online bank that caters to DIY investors and find that investors who self-select into crypto investing are more risk taking and more bias prone. Pursiainen and Toczynski (2022) use data from a US Fintech firm to track transfers in and out of crypto exchanges. They confirm that users who enter into cryptos tend to be younger, more affluent, and are more likely to be male. Using a related approach, Di Maggio et al. (2022) identify flows to and from crypto exchanges and show that crypto investors initially tended to be more sophisticated and hold larger investment accounts, but over time, crypto entrants' became less wealthy. Auer et al. (2023) analyze data from an app-tracking platform and relate crypto price movements to user adoption of cryptos and demographics. These studies establish the emergence of crypto investment among households, thus supporting the motivation for our paper. Unlike our paper, they generally do not observe trades and focus on the initial decision to adopt (or exit) cryptos. Overall, they find that past returns matter for adoption, thus providing complementary analysis to our paper. 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. Our paper also relates to the work of Carleton Athey et al. (2016), Griffin and Shams (2020), and Makarov and Schoar (2020). While data from retail traders on centralized exchanges, like eToro, only constitute a subset of trades in crypto markets, it can potentially help inform broader dynamics in these markets.

3. Data

Our data is from eToro, a global brokerage platform founded in 2007. As of 2019, the last year of our sample, it had 12M registered users and 0.5M funded accounts across more than 100 countries.[7] eToro enables users to trade in a diverse range of asset classes, including currencies, commodities, equity indexes, individual equities, and more recently, cryptocurrencies. Trades are frequently executed through Contracts for Difference (CFDs), which pay the difference in the settlement price between the opening and closing trades of the underlying asset. The use of these contracts allows eToro to implement trades that are small in size and enables users to take on leverage.

In our data we observe retail traders' demographic characteristics (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 ("gurus") by selecting to follow them. In this paper, we focus on self-initiated trades

[7] See https://www.sec.gov/Archives/edgar/data/1493318/000121390021026490/filename1.htm.

in stocks, cryptocurrencies, and gold. Our data spans the period of 1/1/2015 through 12/15/2019.[8] We focus on investors that have traded either cryptocurrencies or stocks at least once during their tenure on eToro, which results in a sample of 199,927 investors that we study in this paper.

As Figure 1 shows, in line with the price appreciation in cryptocurrencies, eToro experienced strong growth in cryptocurrency investing beginning in 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 dollars invested on eToro in our sample. When the price dropped at the beginning of 2018, the amount of dollars invested in cryptocurrencies also declined and stabilized around 20% of total investments made on eToro. A similar shift toward cryptocurrency 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 cryptocurrencies were nearly identical[9]). As Figure 1 shows, the dollar amount invested in currencies was quite high on the platform early on, reaching almost 70% at the beginning of 2015, but steeply declined over the next two years. By 2017 the dollar amount invested in currencies dropped to around 10% of total investments on eToro, and stayed at this level. In contrast, the amount invested in commodities increased slightly over the time period, from about 10% 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 in commodities on gold, especially in light of the narrative that draws parallels between cryptocurrencies and gold. We will abstain from looking at currency trades, since trading in currencies has been relatively small since 2017. Furthermore, given the international nature of the eToro platform, it is difficult to know which of these trades are for investment and speculative purposes and which are used to hedge real-currency exposures.

Figure 2 and Table 1 provide summary statistics for the 199,927 traders in our final sample. Figure 2, displays the residency of the traders in our dataset. Overall, we observe users from more than 100 countries. We report the top ten countries, and collapse the rest into the "Other" category. As the figure shows, the majority of investors come from European countries (UK, Germany, Italy, etc.), with some coming from 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

[8]eToro shared with us data on users who, at some point in time, followed at least one guru. This could lead to a selection bias, as investors who follow a guru at some point might be different than investors who never follow a guru. However, our finding that the investors in our sample have a similar trading strategy in stocks to investors on Robinhood (using data from RobinTrack) and to investors studied in Luo et al. (2020), alleviates some of the selection bias concern.

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

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 was around \$494 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 daily account balance was a little under \$1,000, which is a significant proportion of their liquid assets. The median holding period was 12 days for cryptos and 7 days for stocks.

Panel B of Table 1 reports the summary statistics for the log of daily returns plus 1, for the assets we study, during our sample period. The average log daily return in the sample is zero for the top 200 stocks traded on eToro and also zero for gold, but slightly positive for cryptocurrencies, with a mean log daily return of 0.002. The standard deviation of the log daily returns is also much higher for cryptocurrencies (0.053) compared with stocks (0.027) and gold (0.006).

3.1 Representativeness

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 our dataset is difficult. To address this question we use retail trading data from NASDAQ and Robinhood to compare the trading behavior of eToro investors to that of US retail investors. We find that the two are highly correlated in the time series and cross-section.

Specifically, we first 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 volume of retail investors in a given ticker divided by total dollar volume of retail investors across all tickers, and "sentiment", defined as the retail net flows (buys minus sells) 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 frequently used by retail investors (Cookson et al. (2022)).

We also obtain data on Robinhood traders from Robintrack.net.[10] We use the data from May 2018,

[10] https://robintrack.net/.

when Robintrack data becomes available, through Dec 2019, when our eToro dataset ends. Robintrack provides the unique number of Robinhood users holding a given ticker on a given day. We focus on the top 200 stocks in the eToro dataset and construct a parallel measure of unique investors holding a given ticker 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 at similar times as retail investors on Robinhood.

3.2 Cohort Level Data

To smooth out the noise in the trading behavior of individual investors, and to focus on their fundamental reasons for trading, we construct portfolios of various subsets of users (representative investors) and measure changes to these aggregate portfolios on the daily level for each stock, cryptocurrency, and gold. This approach to data is similar to sorting individual stocks into portfolios in asset pricing tests, which is routinely used to reduce the impact of idiosyncratic noise on parameter estimates. We perform heterogeneity tests by focusing on 'representative agents' from different cohorts (e.g., age, wealth, etc).

4. Theoretical Framework and Variable Construction

In this section, we develop a model that connects investors' portfolio decisions to past asset returns. The model is set in discrete time and consists of two main components: (1) portfolio policy and (2) belief dynamics. There are n risky assets and one riskfree asset available for investment. As in Campbell and Viceira (2002), returns are lognormally distributed and investors have power utility functions with a relative risk aversion coefficient γ. Since most trades in our data have a short horizon, we assume that investors follow a myopic portfolio policy so their vector of optimal portfolio weights (see Campbell and Viceira (2002) for more details) evolves according to

$$\mathbf{w_t} = \frac{1}{\gamma}\Sigma_t^{-1}(\mu_t - \mathbf{1}r_{f,t} + \sigma_t^2/2), \tag{1}$$

where $\mu_t = E_t\mathbf{r_{t+1}}$, $\Sigma_t = Cov_t(\mathbf{r_{t+1}}, \mathbf{r_{t+1}})$, $\sigma_t^2 = Var_t(\mathbf{r_{t+1}})$, $\mathbf{1}$ is a vector of ones, and $\mathbf{r_t}$ is the vector of log return on the risky assets.

Equation (1) shows that the portfolio weights can change if there is a variation in either the first or the second moments of asset returns, or in the level of the riskfree rate. Since the riskfree rate and the variance of returns are highly persistent processes, we assume in the subsequent analysis that both the risk-free rate and the variance-covariance matrix of returns remain constant. Consequently, any changes in portfolio weights are triggered solely by variations in expected returns.

Portfolio policy (1) implies that when investors have more optimistic expectations about the return on a certain asset, the weight of this asset in their portfolio increases, that is, $\frac{\partial w_{it}}{\partial \mu_{it}} > 0$, $i = 1, .., n$. This follows from the fact that Σ_t^{-1}, being a positive-definite matrix, has positive diagonal elements.

Having established the connection between portfolio weights and investors' beliefs, we next specify the dynamics governing investor beliefs about expected returns. Addressing this question in full generality is beyond the scope of this paper. In particular, we do not take a stand on the ongoing debate of whether investors are rational or are influenced by various behavioral biases. Here, we focus only on the role of past returns for investors' beliefs. Specifically, we assume that investors believe that the expected return on asset i at time t is determined as

$$\mu_{it} = \mu_i + \sum_{s=0}^{T} \alpha_{is} r_{i,t-s} + \varepsilon_{it}, \tag{2}$$

where μ_i is a constant, $r_{i,t-s}$, $i = 0, .., T$ is a vector of realized returns from time $t - T$ to time t, and ε_{it} is the cumulative effect of any factors not captured by the returns.

Despite its simplicity, model (2) nests several important cases. First, it accommodates the case where investors are rational and returns follow an $AR(n)$ process, $n < T$. Second, equation (2) can be used to model extrapolative expectations (e.g., Greenwood and Shleifer (2014), Barberis et al. (2018)) and natural expectations (e.g., Fuster et al. (2012), Han and Makarov (2021)). Finally, the model fits many forms of technical analysis, which is popular among retail investors. For example, it is common for investors who use technical analysis to trade based on the deviation of the current price from the exponential moving average price. Notice that we can write this difference as

$$P_{it} - \frac{1-\beta}{1-\beta^{T+1}} \sum_{s=0}^{T} \beta^s P_{it-s} \approx P_{it-T} \left(\sum_{s=t-T}^{t} r_{i,s} - \frac{1-\beta}{1-\beta^{T+1}} \sum_{s=0}^{T} \beta^s \sum_{s=t-T}^{t-s} r_{i,s} \right). \tag{3}$$

Hence, the normalized deviation can be expressed as a function of past returns:

$$\frac{P_{it} - \frac{1-\beta}{1-\beta^{T+1}} \sum_{s=0}^{T} \beta^s P_{it-s}}{P_{it-T}} \approx \sum_{s=0}^{T} \left(1 - \frac{1-\beta^{s+1}}{1-\beta^{T+1}} \right) r_{i,t-s}. \tag{4}$$

Equations (1) and (2) imply that portfolio weights are functions of past returns and that

$$\frac{\partial w_{it}}{\partial r_{i,t-s}} = \frac{\partial w_{it}}{\partial \mu_{it}} \times \frac{\partial \mu_{it}}{\partial r_{i,t-s}} = \alpha_{is} \frac{\partial w_{it}}{\partial \mu_{it}}. \tag{5}$$

Therefore,

$$\frac{\partial(w_{it}-w_{it-1})}{\partial r_{i,t}} = \alpha_{i0}\frac{\partial w_{it}}{\partial \mu_{it}}$$
$$\frac{\partial(w_{it}-w_{it-1})}{\partial r_{i,t-s}} = (\alpha_{is}-\alpha_{is-1})\frac{\partial w_{it}}{\partial \mu_{it}}, \quad s=1,..,T. \tag{6}$$

where we used the fact that $\frac{\partial w_{it}}{\partial \mu_{it}} = \frac{\partial w_{it-1}}{\partial \mu_{it-1}}$.

The system of equations (6) can be estimated using regression analysis. Equation (6) shows that the regression coefficients are the product of α_{it}, that controls the sensitivity of the investors' expectations to asset returns, and $\frac{\partial w_{it}}{\partial \mu_{it}}$, that shows how portfolio weights change in response to changes in the investors' expectations.[11] To reduce the variability of $\frac{\partial w_{it}}{\partial \mu_{it}}$ across different assets and to make the coefficients more interpretable, we use logs of portfolio weights. Provided positive values for portfolio weights, equations (6) imply that

$$\frac{\partial(\ln w_{it}-\ln w_{it-1})}{\partial r_{i,t}} = \alpha_{i0}\frac{\partial w_{it}}{\partial \mu_{it}}/w_{it}$$
$$\frac{\partial(\ln w_{it}-\ln w_{it-1})}{\partial r_{i,t-s}} = \left(\alpha_{is}-\alpha_{is-1}\frac{w_{it}}{w_{it-1}}\right)\frac{\partial w_{it}}{\partial \mu_{it}}/w_{it} \approx (\alpha_{is}-\alpha_{is-1})\frac{\partial w_{it}}{\partial \mu_{it}}/w_{it}, \quad s=1,..,T. \tag{7}$$

One complication in using changes in portfolio weights as indicators of shifts in return expectations could arise if investors do not pay attention to their portfolios or the underlying asset prices. In such instances, they may fail to optimize their portfolios in response to price changes. For example, a lack of rebalancing could mechanically increase asset shares in the portfolio following positive returns, even if investors have not updated their return expectations. To see this, notice that we can write the change in the portfolio weights as

$$\ln w_t^i - \ln w_{t-1}^i = \ln\frac{X_{it}P_{it}}{W_t} - \ln\frac{X_{it-1}P_{it-1}}{W_{t-1}} = a_{it} + r_{i,t} - r_t^W,$$
$$a_{it} = \ln X_{it} - \ln X_{it-1}, \quad r_{i,t} = \ln P_{it} - \ln P_{it-1}, \quad r_t^W = \ln W_t - \ln W_{t-1}, \tag{8}$$

where X_{it} is the number of shares of assets i held by the investor at time t, P_{it} is the price of risky asset i, and W_t is the investor's wealth.

Following Calvet et al. (2009), we define $a_{it} = \ln X_{it} - \ln X_{it-1}$ as the active share change. Equation (8) provides a decomposition of the total share change into the active share change, which isolates the effect of trading, and the passive component $r_{i,t} - r_t^W$. The passive component shows that the port-

[11] An implicit assumption in this analysis is that returns on different assets are uncorrelated. We extend the results to include correlated returns in Appendix B.

folio weights change in response to asset returns even if the investors do not rebalance their portfolios. In particular,

$$\frac{\partial(\ln w_{it} - \ln w_{it-1})}{\partial r_{i,t}} = \frac{\partial a_{it}}{\partial r_{i,t}} + \frac{\partial r_{i,t}}{\partial r_{i,t}} - \frac{\partial r_t^W}{\partial r_{i,t}} = \frac{\partial a_{it}}{\partial r_{i,t}} + 1 - w_{it}. \tag{9}$$

Therefore, a positive sign on the total share change could be consistent with limited attention or investors positively updating their expectations.

Notice that the model's conclusions remain valid when evaluated at times when investors are actively paying attention to their portfolios. Consequently, to demonstrate that our results are not influenced by limited attention, the empirical analysis detailed in Section 5 employs active share change as a dependent variable. This approach helps to exclude inattentive and passive changes in portfolio weights. Additionally, we monitor trading activities to identify instances when investors are actively engaged with their portfolios.

5. Results

We now analyze the trading behavior of the retail investors in our sample as a function of contemporaneous and 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:

$$\begin{aligned} \log(ShareChange_{t,i}) = \alpha_i + \beta_1 \log(Ret_{t,i}) + \beta_2 \log(CRet1Week_{t,i}) + \beta_3 \log(CRet1Month_{t,i}) \\ + \beta_4 \log(CRet3Month_{t,i}) + \beta_5 \log(CRet6Month_{t,i}) + \gamma X_{i,t} + \epsilon_{i,t}, \end{aligned} \tag{10}$$

where i represents a given stock, cryptocurrency, or gold. $ShareChange_{t,i}$ is either the total share change or the active share change. As defined in Section 4 Eq. (8), Log(Active Share change) can be written as log(Shares owned$_t$) − log(Shares owned$_{t-1}$) and Log(Total Share change) can be written as log(Active Share Change$_t$) + $\log(Price_t/Price_{t-1}) - Log(Wealth_t/Wealth_{t-1})$. [12] In all our analysis we assume that α_i are the same for all assets within an asset class.

We include contemporaneous as well as lagged cumulative 1 week, 1 month, 3 month, and 6 month returns as controls. The cumulative returns are calculated starting from day $t-1$. These are calculated as overlapping returns to mimic time periods that might be salient to investors. For each asset class,

[12] $Wealth_t$ is the portfolio value at the end of day t, which includes the value of the individual assets that the investor holds marked to market at the end of day t, as well as any cash she has in her account with eToro.

we run separate regressions with total share changes and with active share changes as the dependent variable. For the active share change regressions, we also control for returns on wealth and on any cash inflows ($\gamma X_{i,t}$). We don't use those controls for the total share change, as they are highly correlated with the dependent variable. The standard errors are clustered by date and the focus of the analysis is on a comparison between stocks, gold, and cryptocurrencies 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 Section 3.2. 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 cryptos by trading volume in our sample: Bitcoin (BTC), Ethereum (ETH), and Ripple (XRP). The change in the total share for cryptocurrencies is strongly, positively related to same-day returns and more weakly related to the last 1 week log cumulative returns. In particular, a 1% increase in contemporaneous returns is associated with a 0.67% increase in the total portfolio share of cryptocurrencies. Beyond a week there is no economically meaningful relationship, with further out returns and the estimated coefficients are close to zero.[13] 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 the magnitude of the estimated coefficient on the same-day returns are similar for days with positive versus negative returns. One small difference is that for days with positive returns the one week lagged return also has a positive and borderline significant relationship, but the magnitude of the effect is much smaller than that of the contemporaneous return. In contrast, for days with negative returns only the contemporaneous returns are significant. Overall these results suggest that retail investors are willing to increase their total portfolio share in cryptocurrencies after a price increase. In columns (4) through (6) we then repeat the same regression specifications but use the log of the change in the active share as the dependent variable. 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 for all observations and positive returns. It is slightly negative for negative returns, but the magnitude of the coefficient is small. The coefficients for 1-week lagged cumulative returns are positive and significant with small coefficients. These results suggest that investors are not actively re-balancing out of cryptos in response to price changes and, if anything, are moving more money into cryptocurrencies as the prices increase with a one week lag.

It is important to note that even though we are examining contemporaneous returns and share

[13] We also estimate these regressions separating out returns one day out, two days out and so on for the whole week. However, the results do not materially change.

changes, it is unlikely that our results are driven by reverse causality. As the summary statistics demonstrate, investors in our sample are very small and are unlikely to be moving prices.

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 ensure that we have enough trading activity on a day-to-day basis.[14] In column (1) the coefficients on the contemporaneous log returns and the one-week lagged cumulative returns are negative, which means that retail traders actively reduce exposure to stocks whose price appreciates and increase exposure to stocks whose price depreciates. When we break out the results into positive and negative return dates, we find the identical response on positive-return and negative-return dates. 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). In particular, a 1% increase in contemporaneous returns is associated with a 1.2% decrease in the portfolio share due to rebalancing, which translates to a 0.28% decrease in total portfolio share of stocks. 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, our results imply that returns have a strong, persistent effect on total portfolio shares and that investors appear to be contrarians when trading stocks but not when trading cryptocurrencies.

In Panel C of Table 3 we repeat the same analysis for investments in gold. Here we see strong contrarian trading, with the coefficients of total share changes on log contemporaneous returns being almost the same size as the coefficients for active changes. In particular, a 1% increase in contemporaneous returns is associated with a 38.1% decrease in the portfolio share due to rebalancing, which translates to a 37.3% decrease in total portfolio share of gold. While these magnitudes are quite large, it can be explained by gold returns having much lower volatility than other asset classes (as shown in Table 1 Panel B). A 1% increase in gold returns is historically very large. This lower variability in gold returns prompted eToro to offer much higher leverage for gold than for other asset classes. In our data, the average leverage in gold positions is much higher than the average leverage in stocks and cryptos (46.3 in gold, versus 3.9 in stocks, and 1.1 in cryptos). In the Appendix Table A2 we examine how different levels of leverage in gold affect how much individuals react to price changes. In Panel A we examine trades with leverage of 20 and below (which make up 41% of all trades in gold) and in Panel B

[14]For the list of the top 200 stocks by eToro trading, refer to Appendix Table A1. We also repeat the analysis for different subsets of the data, e.g., the top 50 or all stocks and the results are qualitatively similar.

trades with leverage of 50 and above (which make up 51% of all trades in gold). The average leverage in Panel A is 16.6 and in Panel B it is 74.9. Results from the two panels suggest that the coefficients increase with leverage. Therefore, while the coefficients in Panel C of Table 3 appear large, accounting for differences in leverage, the coefficients on gold are more comparable in size to coefficients on stocks and cryptos.[15]

Given the differences in leverage investors assume across different asset classes, we also rerun our analysis while accounting for it directly. When calculating the number of shares of a given asset an investor owns at any given time, we multiply the number of shares they buy or sell by the leverage of the trade. I.e., if an investor buys 10 BTCs with leverage of 2, we record it as her having bought 20 BTCs. We rerun the analysis similar to Table 3, and the new results are presented in Table A3 in the Appendix. Given that the majority of trades in cryptocurrencies don't take on any leverage (the average leverage is 1.1), it's not surprising that the results for crypto are similar to the main results in Table 3 Panel A. When examining the results for stocks in Panel B, we find that adjusted for the leverage investors take on, the effects are even stronger - a 1% increase in contemporaneous returns is associated with a 1.58% decrease in the portfolio share due to rebalancing, which translates to a 0.644% decrease in total portfolio share of stocks. Finally, when looking at gold in Panel C, we find that the effects get stronger, compared to our main specification, but not considerably so. Overall, we find that adjusting for leverage doesn't qualitatively change our results. If anything the trading in stocks and gold is even more contrarian, while the results for cryptos are virtually unchanged.

Taken together, the results above support the view that cryptocurrencies are indeed being traded differently from stocks and gold. At least when it comes to how retail investors trade, crypto does not seem to be the new gold. Furthermore, since we regress logs on logs in Table 3, our results can also be interpreted as elasticities. In particular, results in Panel A, show that for cryptocurrencies, total share change has an elasticity of 0.67, whereas for stocks it is -0.28. These differences stem from the fact that retail investors barely rebalance their crypto holdings in response to crypto price changes, whereas they have a strong contrarian rebalancing (elasticity of -1.2) in response to changes in stock prices. For gold the effects are particularly strong (elasticity of about -37), which in part stems from much larger leverage investors take in gold, as we describe above.

Extreme Realizations of Returns. To further understand the different nature of trading strategies across stocks, gold, and cryptocurrencies, we test whether the effects are driven by days with extreme price movements. It could be the case that investors only rebalance when returns are either very high or very low. For this analysis, we repeat our main specification but divide the sample into quintiles based

[15] We thank an anonymous referee for pushing us to dig deeper into the differences between gold and stock trading.

on the within-asset class contemporaneous day returns. The difference in the distribution of returns for stocks, gold, and cryptocurrencies is quite large, with the latter, on average, more volatile and more skewed, as seen in Panel B of Table 1. In our sample period, the 20% (80%) percentile of daily returns for stocks was -1.1% (1.2%), for gold was -0.41% (0.38%), while for cryptocurrencies it was roughly double the one for stocks: -2.5% (2.9%).

Panel A of Table 4 reports the results on the total share and Panel B on active share. In Panel A, for cryptocurrencies we see that the total share moves particularly strongly when returns are in the bottom and the top two quintiles, i.e., quintile 1 for the worst performance days and quintiles 4 and 5 for the best performance days. The relationship is insignificant for the middle quintile. The magnitudes are similar to the ones in Panel A of Table 3. However, in Panel B, we see that throughout all quintiles there is no differential re-balancing in response to contemporaneous 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 return quintiles, the picture is quite different. Investors are much more contrarian on extreme positive or negative return dates, with much bigger magnitudes as the results in Panel B of Table 3. In particular, a 1% increase in returns is associated with a 1% decrease in the total portfolio share for the extreme negative and extreme positive returns. When looking at active re-balancing in Panel B, we see a strong contrarian trading response in the top and bottom quintiles, while the estimated effect is much weaker and even positive in the middle quintile (but not significant).

Finally, in gold, we see a contrarian behavior in the extreme negative and positive quintiles. However, similar to the results in Table 3, the magnitudes are much larger than a response to a similar change in returns for stocks. In sum, this suggests that the contrarian trading in stocks and gold is particularly concentrated on days with large price movements, either positive or negative. In contrast, for cryptocurrencies there is no significant change in active re-balancing, independent of the return size, suggesting that investors do not re-balance even after large price movements.

Since retail investors exhibit contrarian trading strategies in both stocks and gold, in the following analysis we will focus on the dichotomy between stocks and cryptocurrencies only, to reduce the size of the tables we present.

5.1 Asset or trader driven?

A natural question when interpreting the above differences in trading behavior for stocks and cryptocurrencies is whether these results are driven by self-selection of investors with different preferences into different asset classes, or by different belief-formation models across these assets. After all, investors are not randomly assigned to trading stocks or cryptocurrencies. 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 during their tenure at eToro, traded both stocks and cryptocurrencies, versus those who always exclusively traded either 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 setup is exactly the same as in Table 3, but we form a the 'representative investor' based on the above-mentioned users only, and we only report the coefficient on the log contemporaneous returns, since the lagged returns are not significant (even though we always control for them). As in the sample with all traders, we see the stark dichotomy: investors are contrarian in stock trading but momentum-like 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. Furthermore, similarly to Table 3, the analysis of the active share change shows that these investors actively re-balance out of stocks during periods of positive returns and into stocks during periods of negative 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 cryptos or stocks during their tenure on eToro. Here we again see in Columns (1) through (3) that traders who exclusively trade in crypto are momentum-like traders, i.e., their total share changes positively with log returns. When looking at the active share change, we see that they do not re-balance in response to price changes. In Columns (4) through (6) we focus on investors who exclusively 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. However, on days when returns are negative they do not seem to rebalance and thus their total share goes down as well. Overall, their investment strategy is momentum-like, but only weakly so, compared to the coefficient magnitudes for exclusively-crypto and both crypto-and-stock traders.

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

5.2 Investor Heterogeneity

While we have shown that the dichotomy in trading behavior of stocks and cryptos 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 subgroups of crypto-currency investors who display this difference in trading behavior across different assets. For this purpose, we next examine 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), finance experience ('Finance Background' 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 whether the trader has ever been a 'guru' (had copiers) during their tenure on eToro. 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 interaction terms of the log same-day returns and log past cumulative returns with the characteristic in question. In Panel A we focus on the changes in the total share and in Panel B on the changes in active share, or rebalancing.

Overall the analysis of personal characteristics shows that all groups are quite similar in their trading behavior. In Panel A, when examining the total share change, the coefficient on log returns is positive and significant for crypto trades and consistently negative and significant for stocks. In Panel B, the coefficients on log returns are zero for cryptos and consistently significantly negative for stocks. For both panels, the interaction terms with different investor types are generally insignificant. In other words, the dichotomy between being momentum-like in cryptos and contrarian in stocks is robustly present across traders and it is not driven by a specific subset. This is consistent with findings in Giglio et al. (2021), who find that demographic characteristics do little to explain differences across investor beliefs. We do find that some groups are less muted in their responses. For example, when looking at cryptocurrencies, we find that investors with lower wealth react slightly less to same-day returns and are thus slightly less momentum than more affluent investors. This holds for the change in total share and active share. When looking at some of the most successful investors on the eToro platform, called gurus, we see that they are more momentum in cryptocurrencies. Additionally, the effect is small relative to the magnitude of the coefficient for non-gurus. In sum, there is quite a lot of similarity in how different types of investors trade in crypto-currencies versus in other assets.

5.3 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 in Section 4, 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 trade out of stocks when their prices go up and into stocks when prices decrease. Thus, inattention would have to only apply to cryptocurrencies 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. However, to test this channel more directly, we repeat the analysis from Table 3, but form investor cohorts based on how active they have been on eToro at a given point in time: we define *active* users as users who traded at least once during the previous seven days (in any asset), while *inactive* investors are defined as not having traded in any asset in the past 30 days. We only focus on investors who have been on eToro for at least 30 days.

Table 7 reports the results. In Panel A, we find that for the group of active investors the results are parallel to our main results: the total share change is positive for cryptocurrencies and strongly negative for equities. The coefficients are similar in magnitude for cryptos to our main results and are slightly stronger for stocks. When looking at the active share change for these attentive investors, we find that they are not re-balancing their crypto holdings actively in response to price changes but are active in their stock investments. However, when we look at the inactive investors in Panel B we see an interesting difference: the total share change moves positively with contemporaneous returns for both stocks and cryptos. In other words, they are momentum in both of these asset classes. Even the magnitudes are similar for both asset classes. We furthermore find that for the inattentive investors the active share change coefficient on contemporaneous returns is close to zero for both stocks and cryptos, which explains the momentum-like trading behavior in the total share change. This suggests that our metric of inattention seems to be effective at filtering out investors who do not pay attention to their portfolios and therefore their total portfolio share of those assets moves up and down passively with price changes. Most importantly, the results suggest that even *attentive* investors still display a strong dichotomy in crypto versus stock investments, mirroring our main specification results.

To focus even more on investors who are active, in Appendix Table A4 we examine investors who traded in any asset on day t, rather than in the past seven days. While we lose a lot of observations, we find that the difference between trading in cryptos and stocks becomes even more stark. Thus, the momentum-like trading behavior in cryptos is due to investors actively not rebalancing rather than to investors not paying attention.

Next, we examine whether our results are driven by attentive investors who might not care about crypto returns since cryptos make up a very small fraction of their overall portfolio. In Appendix Table A5 we focus on investors who have traded any asset in the past 7 days, and also had at least 30% of their portfolio invested in cryptos and at least 30% invested in stocks at time $t-7$. In other words these investors had skin in the game in both assets. When looking at their rebalancing, we find that these investors are slightly less contrarian in stocks, but are still actively not rebalancing in cryptos, even though they are paying attention and have a large fraction of their portfolio invested in this asset class. To sum up, the results in this section suggest that the dichotomy in the investment strategies between stocks and cryptos is not driven by inattentive investors or investors who do not have skin in the game in the given asset class.

5.4 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 crypto trading and other assets. In order to control for such early adoption concerns, we repeat our main analysis, 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. Table 8 Panel A reports the changes in total share, for cryptocurrencies and stocks, and Panel B reports the changes in the active share. We see that the results are virtually unchanged from Table 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.

Individual Transactions. Next, we confirm that our results are not driven by the cohort-level aggregation that we propose 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 earlier, we include only the top 50% of investors in our sample, based on the number of days investors traded in either cryptos or stocks. We focus on investors who traded in both cryptos and stocks during their tenure at eToro. Our final sample consists of 58,954 users and with over 39 million trades. We re-run 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 include individual fixed effects, to analyze the changes within a person over time, as well as date and asset fixed effects. We find similar results to our main specification. With respect to contemporaneous returns, investors are contrarian in their total portfolio share for stocks and momentum in the total portfolio share for cryptos. The magnitudes on total portfolio share changes are also similar in cryptocurrencies to the magnitudes in the aggregated analysis. The magnitudes for stocks are larger for positive returns and smaller for negative returns than in the aggregated analysis. Overall, this suggests that our results are not distorted by the aggregation into cohorts.[16]

Transaction Costs. Transaction fees on eToro have been changing over time and across different asset classes. Next, we make sure that the momentum-like trading strategy in cryptos is not driven by investors not rebalancing as often due to high transaction costs in cryptocurrencies. While we don't have the full history of transaction cost changes for all asset classes, we examine whether differences in transaction fees are driving the different trading strategies from several different angles. First, if higher trading costs caused investors not to rebalance cryptos as often, we would expect them to rebalance more when returns are higher, and thus the benefit of rebalancing exceeds the cost. Yet, in Table 4 Panel B we observe that investors do not actively rebalance their crypto holdings, even on days when returns are either very high or very low (top/bottom quintiles). Second, in April/May 2019, eToro removed trading fees for non-levered stock trades in 18 countries.[17] We examine non-levered trades by active investors (who have traded in the past seven days) in the affected countries before April 2019 with their trading behavior after May 2019. We test whether investors started trading more contrarian after the removal of trading fees. If investors rebalanced cryptos less often due to higher trading fees, we would expect them to rebalance more actively in stocks after the removal of fees. The results are presented in Appendix Table A7. 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. Taken together, this evidence suggests that higher trading fees are not the main driver of investors' momentum-like trading in crytocurrencies.

Individual Assets. To ensure that our results are not driven by any one asset, in Appendix Table A8 we replicate our main specification separately for Bitcoin, Ripple, Ethereum, and for the top three stocks by dollar amount invested on eToro (Tesla, Amazon, Apple). We see that investors do not actively rebalance in BTC, ETH, and XRP, and therefore, their total portfolio share follows a momentum-like pattern. Whereas investors rebalance contrarian in the most-traded stocks. The results suggest that the dichotomy in trading strategies between cryptos and stocks is not driven by any individual asset.

[16]One concern is that while the total shares are almost always positive in the aggregate analysis, they can be either 0 or negative at the individual level. Therefore, by taking logs we end up focusing on the time periods, where the individuals are holding the asset. In Appendix Table A6 we repeat the individual analysis without taking logs.

[17]For more details about the removal of trading fees for stocks on eToro see Even-Tov et al. (2022).

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, investors might think that the best way to be invested in cryptos is to buy and hold the asset class, since returns among cryptos are quite correlated. Whereas in equities there are more *perceived* gains from trading between individual securities. 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 also 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 to examine the concern that investors just trade out of one stock and into another due to perceived gains. When investors make the first purchase in an asset class, they are buying either using existing cash or proceeds from a sale of an asset from a different asset class. The results are presented in Appendix Table A9. We find that investors enter the crypto asset class on days with positive returns and enter the stock asset class on days with negative returns, suggesting momentum-like trading for cryptos and contrarian trading for stocks. Taken together, these findings suggest that our results are not driven by the different number of assets in each asset class.

Leverage. When investors on eToro take on leverage or sell short, they trade contracts for difference which, effectively, bundles the underlying position with leverage. Overall, 85.64% of cryptocurrency trades and 39.41% of stock trades do not use leverage. Given that accounts are marked to market daily, investors might have a different trading strategy for those trades compared to regular, unlevered trades. Therefore, our results could be driven by investors taking on more leverage or trading contract for difference more often in cryptos than in stocks. There are several reasons for why this is unlikely the main driver of our main results. First, similar to Luo et al. (2020) where investors' trades are unlevered, 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 Appendix Table A10, we focus only on trades that do not have leverage, and find similar results to our main specification - momentum-like strategy in cryptocurrencies and contrarian in stocks.

6. Why are cryptos different – Potential Mechanisms

Next, we try to shed some light on why investors differ in how they form price expectations for cryptocurrencies 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) 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 for changes in the probability of future adoption. In other words, when the price of cryptocurrencies goes up for any reason, investors might believe that a higher price makes it more likely that other investors, or even regulators, look more favorably at cryptocurrencies going forward, which would lead to an amplification effect in the price. This type of belief structure could explain the momentum-like trading behavior displayed among the retail investors in our data. This same amplification effect is not present in stocks or gold, since the adoption occurred a long time ago.

However, there are a number of alternative channels that could potentially explain our results. First, prior to 2018, investors had not experienced a crash in cryptocurrencies and thus might have been 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 crashes. The beginning of 2018 saw 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 repeat our analysis from Table 3, using only investors who traded in the seven days prior to ensure that these are investors who actively engage with their portfolios. In addition, we include an interaction term of log contemporaneous and past cumulative returns with a dummy for the post-February 2018 period ("After Crash"). In Panel A we examine the changes in the total portfolio shares and confirm as previously found that for cryptocurrencies, investors follow a momentum-like strategy pre-2018, i.e., the coefficient on log returns is positive and very significant. We find that after the crash investors are still following a momentum-like strategy even after they have seen that prices of cryptocurrencies can drop fast.[18] This interpretation is confirmed in Panel B where we look at the active share before and after the 2018-crash, and find that investors' strategies do not change much after the crash.

In Appendix Table A11 we also analyze if certain subgroups of traders were more likely to change their momentum-like strategy in crypto-trading after the experience of the crash. For this purpose we interact the post crash $\times$ log return term with the same individual characteristics that we use in Table 6. We do not find that there are any subgroups of traders that show significantly larger sensitivity to the crash. The one exception are the so-called 'guru' traders, who became even more momentum-like

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

after the 2018 bubble burst. 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.

Skewness of Returns. An alternative explanation for the dichotomy between trading strategies in cryptocurrencies versus stocks could be that investors are holding on to assets that have 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) and 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 investor participation and skewed returns.

In other words, what might be special about cryptocurrencies is just the nature of the observed returns. However, in that case any other asset with skewed returns would be treated similarly. It would be strange if this preference for skewed returns differed across asset classes. To test the validity of this hypothesis, we utilize the cross-section of stock returns and examine whether stocks that are often seen as being more lottery-like, for example those that have higher volatility, skewness, or are issued by younger firms induce also more "crypto-like" trading behavior. We again focus on investors who have traded both cryptos and stocks during their tenure at eToro. The stock characteristics we measure are return volatility, skewness of daily returns, and the maximum daily return, all measured over the last calendar 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 of contemporaneous and lagged returns 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. When using return volatility or return skewness as the measure of heterogeneity, we find, if anything, that investors are more contrarian on these stocks. Finally, we do not find a significant difference for stocks based on their age and gross profitability. In total, we do not find consistent evidence to suggest that investors are more momentum in all assets with skewed or volatile returns. Rather this momentum-like strategy seems to be unique to cryptocurrencies.

Lack of cash flow information. Finally, one major 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 across different asset classes. For example, Luo et al. (2020) find that retail traders' contrarian trading intensifies in response to earnings announcements. Cash flow news might trigger a re-evaluation of investor beliefs about whether the stock price is too high or too low. If investors believe that others overreact to news, the contrarian trading strategy after earnings announcements follows from their desire to take advantage of that overreaction. The same dynamic would not be at play in cryptocurrency prices which lack regular cash flow news.

In Table 12 we 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) through (3), and to non-earnings-announcement days in columns (4) through (6). Similar to Luo et al. (2020), we define earnings announcement days as 3 days before and 5 days after an earnings announcement, and non-earnings announcement days are defined as all other days. We again look at changes in the total portfolio share 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 overall for both the total share change and the active share change. 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 full 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 Appendix Table A12, but focus only on active investors, defined as having traded any asset on eToro in the prior seven days. We find that the results are significant even on non-earning-announcement days.

Furthermore, gold also does not have cash flow news similar to earnings announcements, yet we observe a contrarian trading behavior. Put together, our evidence does not suggest that the differences in trading behavior between cryptocurrencies and stocks are driven by the difference in cash flow news.

7. 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 stocks and gold. The same set of investors who adopt a contrarian strategy when investing in stocks or gold, show a momentum-like strategy when investing in cryptocurrencies. We also show that the momentum-like trading in cryptocurrencies is mainly driven by the fact that retail investors are willing to hold onto their cryptocurrency investments even in the face of large price swings. They are not actively rebalancing out of them when prices rise sharply nor do they buy up more when the prices drop. We confirm that this dichotomy in trading behavior is not driven by composition effects of which investors trade cryptos, nor by inattention to crypto prices where people are passively affected by price swings. 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 small fraction of how people invest in cryptocurrencies. In other words, independent of age, financial sophistication, income and several other characteristics, we observe the same level of momentum-like trading in cryptocurrencies.

What is behind this type of beliefs? One might conjecture that based on the hype around cryptocurrencies, investors have convinced themselves that these are the newest investment vehicles and thus they need to invest in them no matter what the price dynamic is. However, there might be a less sentiment-driven explanation. The value of cryptocurrencies is largely based on expectations about the potential of wider future adoption, which in turn might be influenced by their current value. Positive returns might increase the likelihood that regulators look more favorably at cryptocurrencies, or institutional investors start investing in them. This would create positive (and negative) feedback loops and justify the momentum-like strategies we see in our data. The same price dynamic is not observed in 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 that use aggregate price data and show that cryptocurrency prices react to news about cryptocurrency adoption, see for example Auer and Claessens (2018), Biais et al. (2020), and Liu and Tsyvinski (2021). Since price information is available at much higher frequency than news announcements, for example 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 research 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.

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8. Tables and Figures

Figure 1. **Share of Dollar Amount Invested in each Asset Class over Time**

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

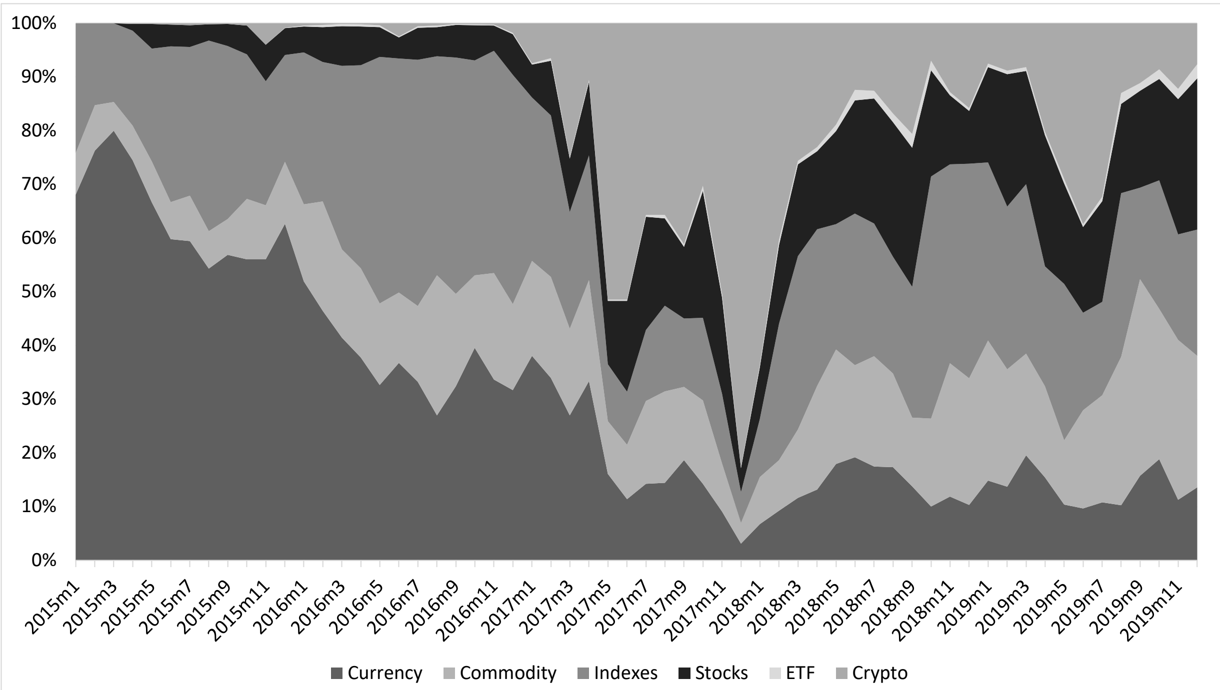

Figure 2. **Investors' Country of Origin**

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.

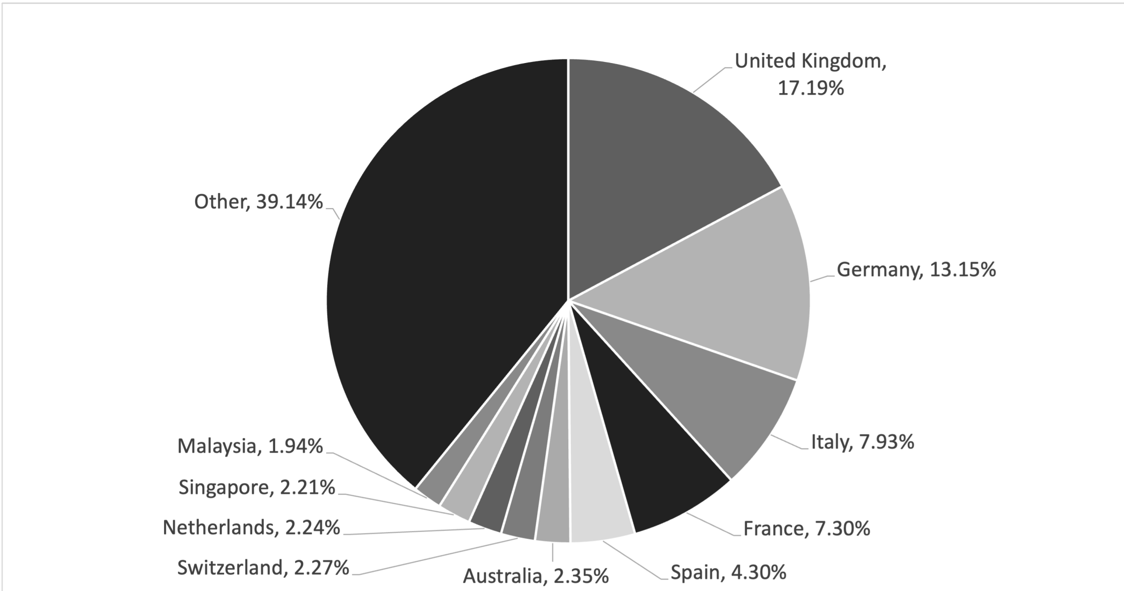

Table 1. **Summary Statistics**

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 reports 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 (an investor with followers) at any point during her tenure at eToro. In Panel B, we show the distribution of log daily 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 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 stocks (\$)	311.30	755.80	1	80	134	285	602	52,234	141,519
Trade size crypto (\$)	494.48	1628.91	1	100	225	421	945	191,863	172,599
Account Balance (\$)	986.99	2042.14	0	60	260	936	2,680	44,837	199,927
Holding period stocks	23.82	55.72	0	2	7	21	57	1,904	141,182
Holding period crypto	57.13	119.32	0	3	12	51	155	1,162	167,690
Frac. invested in stocks	0.13	0.21	0	0	0.02	0.15	0.44	1	199,927
Frac. invested in crypto	0.44	0.37	0	0.05	0.40	0.82	0.96	1	199,927
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)	-0.00005	0.0060	-0.031	-0.0032	0.0000	0.0030	0.0067	0.040	1,356

Table 2. **NASDAQ versus 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. Activity is defined as the dollar volume of retail investors in a given ticker divided by total dollar volume of retail investors across all tickers. Sentiment is defined as the retail net flows (buys minus sells) of the most recent 10 trading days. 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)
R2	0.65	0.35	0.65	0.07	0.03	0.10
Observations	1,125,736	1,125,736	1,125,736	697,016	697,016	697,016

Table 3. **Total 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 cumulative past returns are defined over a time period ending on day $t-1$. *Log*(Ret Wealth$_t$) is defined as $\log([Wealth_t - NetInflows_t]/Wealth_{t-1})$, and log(Ret Net Inflows) is defined as $\log(Wealth_t/Wealth_{t-1}) - \log((Wealth_t - NetInflows_t)/Wealth_{t-1})$. 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 trading on eToro 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)	0.674***	0.727***	0.616***	-0.016	0.001	-0.041
	(0.026)	(0.039)	(0.031)	(0.030)	(0.043)	(0.046)
Log(CR past 1 week)	0.018**	0.037**	-0.002	0.020**	0.032**	0.006
	(0.009)	(0.015)	(0.009)	(0.008)	(0.013)	(0.008)
Log(CR past 1 month)	0.002	0.007	-0.003	0.001	0.002	-0.000
	(0.003)	(0.004)	(0.003)	(0.002)	(0.003)	(0.003)
Log(CR past 3 months)	-0.007**	-0.005	-0.010**	-0.008***	-0.005	-0.011**
	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)	(0.004)
Log(CR past 6 months)	0.006***	0.002	0.008**	0.004**	0.000	0.008**
	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)
Log(Ret Wealth)				0.042	-0.024	0.133**
				(0.043)	(0.059)	(0.062)
Log(Ret Net Inflows)				0.437***	0.454***	0.432***
				(0.102)	(0.148)	(0.154)
R2	0.328	0.378	0.274	0.031	0.033	0.042
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)	-0.282***	-0.263**	-0.298**	-1.207***	-1.259***	-1.346***
	(0.083)	(0.110)	(0.124)	(0.082)	(0.119)	(0.136)
Log(CR past 1 week)	-0.058**	-0.094**	-0.022	-0.059**	-0.100***	-0.019
	(0.026)	(0.039)	(0.032)	(0.025)	(0.037)	(0.032)
Log(CR past 1 month)	-0.021	-0.036*	-0.005	-0.025*	-0.041**	-0.007
	(0.013)	(0.019)	(0.017)	(0.013)	(0.019)	(0.017)
Log(CR past 3 months)	0.010	0.024	-0.003	0.010	0.024	-0.005
	(0.013)	(0.022)	(0.013)	(0.013)	(0.022)	(0.013)
Log(CR past 6 months)	0.005	0.003	0.008	0.007	0.004	0.011
	(0.006)	(0.009)	(0.007)	(0.006)	(0.009)	(0.007)
Log(Ret Wealth)				0.163***	0.086*	0.218**
				(0.054)	(0.046)	(0.088)
Log(Ret Net Inflows)				0.251***	0.549***	-0.126
				(0.082)	(0.106)	(0.130)
R2	0.001	0.001	0.001	0.008	0.007	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)	-37.275***	-36.136***	-36.093***	-38.114***	-36.882***	-39.299***
	(4.549)	(5.203)	(6.994)	(4.585)	(5.649)	(8.802)
Log(CR past 1 week)	1.751*	1.661	1.698	1.752*	1.697	1.588
	(0.920)	(1.257)	(1.293)	(0.918)	(1.259)	(1.318)
Log(CR past 1 month)	0.619	0.137	0.755	0.599	0.068	0.764
	(0.742)	(1.168)	(0.953)	(0.748)	(1.159)	(0.954)
Log(CR past 3 months)	-0.002	-0.836*	0.876**	-0.004	-0.852*	0.881**
	(0.317)	(0.443)	(0.434)	(0.321)	(0.448)	(0.437)
Log(CR past 6 months)	0.006	-0.233	0.218	0.010	-0.212	0.205
	(0.215)	(0.319)	(0.296)	(0.217)	(0.329)	(0.296)
Log(Ret Wealth)				0.252	-0.372	0.850
				(0.486)	(0.644)	(0.732)
Log(Ret Net Inflows)				-0.031	-0.190	-0.569
				(0.839)	(1.109)	(1.503)
R2	0.174	0.170	0.211	0.180	0.176	0.220
Observations	1,356	680	676	1,356	680	676

Table 4. **Return Quintile Analysis**

In this table we examine whether investors respond to returns differently for different return quintiles. We only look at investors who have traded both cryptos and stocks during their tenure on eToro. We generate a representative investor by cumulating trades, net inflows, and wealth, across those investors for each day t. In Panel A we examine Log(Total Share Change$_t$) and in Panel B Log(Active Share Change$_t$), which 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. The log cumulative past returns are defined over a time period ending on day $t-1$. The quintile return 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. *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)	0.685***	0.260	-0.906	1.001***	0.747***
	(0.065)	(0.313)	(1.004)	(0.311)	(0.064)
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)	-1.048***	1.052*	2.328**	-0.574	-1.056***
	(0.275)	(0.550)	(0.906)	(0.716)	(0.248)
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)	-28.206***	-21.748	-37.985	-27.074	-25.261**
	(7.057)	(19.293)	(31.756)	(21.042)	(10.299)
Controls	Yes	Yes	Yes	Yes	Yes
R2	0.058	0.067	0.034	0.006	0.105
Observations	274	274	274	274	274

Panel B

	Log(Active Share Change)				
	Bottom Quintile	2	3	4	Top Quintile
			Cryptos		
Log(Ret)	-0.022	-0.104	-1.596	0.244	-0.034
	(0.055)	(0.221)	(1.422)	(0.292)	(0.073)
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)	-2.028***	0.409	1.417	-1.442**	-2.058***
	(0.273)	(0.548)	(0.903)	(0.714)	(0.248)
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)	-28.456**	-22.988	-36.621	-27.967	-25.656**
	(8.153)	(19.487)	(21.409)	(21.999)	(10.659)
Controls	Yes	Yes	Yes	Yes	Yes
R2	0.076	0.070	0.048	0.007	0.110
Observations	274	274	274	274	274

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 each investor group for each day 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. The log cumulative past returns are defined over a time period ending on day $t-1$. *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: 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)	0.672***	0.752***	0.655***	-0.243***	-0.972***	-0.614***
	(0.026)	(0.047)	(0.044)	(0.088)	(0.147)	(0.169)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
R2	0.292	0.269	0.173	0.000	0.001	0.000
Observations	3,586	1,866	1,720	501,250	261,263	239,987

	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)	-0.022	-0.002	0.007	-1.148***	-1.941***	-1.512***
	(0.030)	(0.048)	(0.050)	(0.088)	(0.146)	(0.169)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
R2	0.021	0.026	0.026	0.002	0.003	0.003
Observations	3,586	1,866	1,720	501,250	261,263	239,987

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)	0.586***	0.668***	0.532***	0.348***	-0.352*	1.040***
	(0.033)	(0.059)	(0.051)	(0.127)	(0.185)	(0.285)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
R2	0.181	0.154	0.112	0.000	0.001	0.001
Observations	3,583	1,866	1,717	337,347	175,448	161,899

	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)	0.015	0.051	-0.070	-0.463***	-1.309***	0.077
	(0.048)	(0.075)	(0.063)	(0.134)	(0.189)	(0.290)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
R2	0.023	0.031	0.033	0.000	0.002	0.000
Observations	3,583	1,866	1,717	337,347	175,448	161,899

Table 6. **Investor Characteristics**

In this table we examine whether there is heterogeneity in how investors trade across different investor characteristics. We generate two representative investors, by cumulating trades, net inflows, and wealth, for each investor group with a given characteristic, or not, for each day t. We only look at investors who have traded both cryptos and stocks during their tenure at eToro. We classify investors as *Female* if she reported being female when signing up with 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 (having followers) 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. All controls are also interacted with the characteristics indicator. The log cumulative past returns are defined over a time period ending on day $t-1$. *Cryptos* are BTC, XRP, and ETH. For the list of the top 200 stocks by eToro trading, refer to Table A1. Standard errors are clustered at the date level and reported in parentheses. Statistical significance is denoted at the ten, five, and one percent levels by *, **, and ***, respectively.

Panel A

	Log(total share change)					
	Cryptos			Top 200 Stocks		
	All	Ret>0	Ret≤0	All	Ret>0	Ret≤0
	(1)	(2)	(3)	(4)	(5)	(6)
Female						
Log(Ret)	0.667***	0.752***	0.650***	-0.341***	-0.815***	-0.498***
	(0.026)	(0.048)	(0.045)	(0.089)	(0.167)	(0.178)
Investor Type	-0.000	0.004	-0.005	-0.005	-0.011*	0.000
	(0.002)	(0.004)	(0.004)	(0.004)	(0.007)	(0.007)
Investor Type × Log(Ret)	0.038	-0.008	-0.013	-0.588**	-0.421	-0.463
	(0.024)	(0.047)	(0.050)	(0.234)	(0.417)	(0.445)
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)	0.661***	0.737***	0.651***	-0.460***	-1.002***	-0.591***
	(0.029)	(0.051)	(0.062)	(0.095)	(0.180)	(0.187)
Investor Type	0.000	-0.000	0.001	-0.002	-0.001	0.003
	(0.001)	(0.002)	(0.002)	(0.002)	(0.005)	(0.004)
Investor Type × Log(Ret)	0.043*	0.063*	0.051	0.400***	0.303	0.661**
	(0.022)	(0.035)	(0.053)	(0.152)	(0.309)	(0.269)
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)	0.682***	0.770***	0.663***	-0.229**	-0.597***	-0.311*
	(0.026)	(0.049)	(0.045)	(0.091)	(0.154)	(0.181)
Investor Type	-0.001	-0.001	0.001	-0.003	-0.001	-0.002
	(0.002)	(0.002)	(0.003)	(0.002)	(0.004)	(0.004)
Investor Type × Log(Ret)	-0.065***	-0.086**	-0.031	-0.152	-0.261	-0.131
	(0.023)	(0.038)	(0.054)	(0.104)	(0.218)	(0.172)
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)	0.682***	0.760***	0.672***	-0.257**	-0.678***	-0.369**
	(0.027)	(0.051)	(0.047)	(0.104)	(0.242)	(0.176)
Investor Type	-0.000	-0.000	-0.001	-0.001	0.002	0.002
	(0.001)	(0.002)	(0.002)	(0.002)	(0.004)	(0.003)
Investor Type × Log(Ret)	-0.034*	-0.020	-0.049	-0.044	-0.249	0.092
	(0.019)	(0.034)	(0.034)	(0.098)	(0.260)	(0.141)
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)	0.665***	0.747***	0.647***	-0.379***	-0.757***	-0.540***
	(0.026)	(0.049)	(0.046)	(0.093)	(0.174)	(0.184)
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)	0.119***	0.093*	0.219***	0.235*	0.095	0.299
	(0.030)	(0.054)	(0.060)	(0.130)	(0.271)	(0.236)
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)	-0.027	-0.003	0.005	-1.258***	-1.779***	-1.430***
	(0.031)	(0.050)	(0.053)	(0.088)	(0.167)	(0.176)
Investor Type	0.001	0.005	-0.003	-0.002	-0.008	0.002
	(0.002)	(0.003)	(0.004)	(0.004)	(0.008)	(0.008)
Investor Type × Log(Ret)	-0.041	-0.026	-0.192*	-0.612***	-0.456	-0.458
	(0.045)	(0.067)	(0.100)	(0.237)	(0.419)	(0.448)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
R2	0.012	0.012	0.021	0.003	0.002	0.003
Observations	7,167	3,732	3,435	303,049	155,969	147,080
			Finance Background			
Log(Ret)	-0.046	-0.023	-0.010	-1.376***	-1.964***	-1.526***
	(0.039)	(0.056)	(0.082)	(0.095)	(0.180)	(0.185)
Investor Type	0.003**	0.002	0.004	-0.001	-0.003	0.008
	(0.002)	(0.002)	(0.003)	(0.003)	(0.005)	(0.005)
Investor Type × Log(Ret)	0.041	0.052	0.032	0.382**	0.289	0.657**
	(0.036)	(0.046)	(0.083)	(0.153)	(0.309)	(0.271)
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)	-0.018	0.012	0.008	-1.149***	-1.561***	-1.246***
	(0.030)	(0.050)	(0.055)	(0.090)	(0.154)	(0.178)
Investor Type	-0.001	-0.001	0.001	-0.003	-0.003	-0.000
	(0.002)	(0.002)	(0.003)	(0.003)	(0.004)	(0.004)
Investor Type × Log(Ret)	-0.074*	-0.095*	-0.048	-0.144	-0.263	-0.115
	(0.040)	(0.052)	(0.079)	(0.106)	(0.219)	(0.173)
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)	-0.025	-0.001	-0.004	-1.181***	-1.645***	-1.306***
	(0.033)	(0.054)	(0.055)	(0.104)	(0.243)	(0.173)
Investor Type	0.000	0.000	-0.002	-0.000	0.005	0.000
	(0.001)	(0.002)	(0.002)	(0.002)	(0.005)	(0.003)
Investor Type × Log(Ret)	-0.012	0.005	0.004	-0.023	-0.244	0.107
	(0.031)	(0.046)	(0.055)	(0.098)	(0.261)	(0.142)
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)	-0.029	-0.010	0.003	-1.296***	-1.727***	-1.470***
	(0.031)	(0.050)	(0.055)	(0.092)	(0.174)	(0.181)
Investor Type	0.004*	0.002	0.008*	-0.007***	-0.005	-0.005
	(0.003)	(0.004)	(0.004)	(0.002)	(0.004)	(0.004)
Investor Type × Log(Ret)	-0.081*	-0.057	-0.030	0.198	0.112	0.252
	(0.049)	(0.058)	(0.121)	(0.132)	(0.273)	(0.238)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
R2	0.006	0.007	0.008	0.005	0.005	0.005
Observations	7,160	3,726	3,434	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. An investor is defined as active if she traded any asset in the prior 7 days, and as inactive if she hasn't traded 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. We generate a representative investor, by cumulating trades, net inflows, and wealth, across these active and inactive investors for each day t. 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. The log cumulative past returns are defined over a time period ending on day $t-1$. *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: 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)	0.690***	0.758***	0.582***	-0.750***	-1.231***	-0.779***
	(0.052)	(0.069)	(0.093)	(0.106)	(0.182)	(0.203)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
R2	0.070	0.067	0.030	0.002	0.002	0.001
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)	-0.012	0.002	-0.012	-1.572***	-2.117***	-1.703***
	(0.032)	(0.062)	(0.064)	(0.100)	(0.179)	(0.194)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
R2	0.016	0.024	0.016	0.008	0.007	0.007
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)	0.940***	1.188***	0.783***	0.959***	0.415	0.643*
	(0.150)	(0.308)	(0.190)	(0.218)	(0.435)	(0.363)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
R2	0.033	0.062	0.026	0.000	0.000	0.000
Observations	3,519	1,834	1,685	86,551	44,545	42,006

	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)	-0.034	0.124	-0.184	-0.037	-0.587	-0.351
	(0.157)	(0.333)	(0.195)	(0.219)	(0.434)	(0.363)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
R2	0.125	0.208	0.104	0.003	0.004	0.003
Observations	3,519	1,834	1,685	86,551	44,545	42,006

Table 8. **Existing Users**

In this table we examine how users trade who have been active on eToro for at least 90 days prior to day t. We only look at investors who have traded both cryptos and stocks during their tenure on eToro. We generate a representative investor, by cumulating trades, net inflows, and wealth, across these investors for each day t. 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. The log cumulative past returns are defined over a time period ending on day $t-1$. *Cryptos* are BTC, XRP, and ETH. For the list of the top 200 stocks by eToro trading, refer to Table A1. Standard errors are clustered at the date level and reported in parentheses. Statistical significance is denoted at the ten, five, and one percent levels by *, **, and ***, respectively.

Panel A

	Log(total share change)					
	Cryptos			Top 200 Stocks		
	All	Ret>0	Ret≤0	All	Ret>0	Ret≤0
	(1)	(2)	(3)	(4)	(5)	(6)
Log(Ret)	0.661***	0.744***	0.659***	-0.407***	-0.955***	-0.496***
	(0.025)	(0.050)	(0.045)	(0.086)	(0.155)	(0.172)
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)	-0.066*	-0.021	-0.060	-1.334***	-1.918***	-1.439***
	(0.034)	(0.056)	(0.047)	(0.086)	(0.155)	(0.169)
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 using account-level data. We only look at investors who have traded both cryptos and stocks during their tenure on eToro. We keep the top 50% of traders by the number of days they traded in stocks and 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. The log cumulative past returns are defined over a time period ending on day $t-1$. *Cryptos* are BTC, XRP, and ETH. For the list of the top 200 stocks by eToro trading, refer to Table A1. 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 individual, asset, and date fixed effects. Standard errors are clustered at the date and individual investor level and reported in parentheses. Statistical significance is denoted at the ten, five, and one percent levels by *, **, and ***, respectively.

Panel A

	Log(total share change)					
	Cryptos			Top 200 Stocks		
	All	Ret>0	Ret≤0	All	Ret>0	Ret≤0
	(1)	(2)	(3)	(4)	(5)	(6)
Log(Ret)	0.638***	0.414***	0.805***	-0.564***	-2.013***	0.261
	(0.060)	(0.135)	(0.090)	(0.140)	(0.202)	(0.227)
Log(CR past 1 week)	0.010	0.060**	-0.024	-0.184***	-0.346***	-0.038*
	(0.017)	(0.027)	(0.027)	(0.019)	(0.033)	(0.022)
Log(CR past 1 month)	0.017**	0.013	0.019*	-0.009	-0.049***	0.020*
	(0.007)	(0.008)	(0.011)	(0.009)	(0.012)	(0.012)
Log(CR past 3 months)	-0.001	-0.004	0.001	0.013**	-0.002	0.031***
	(0.003)	(0.004)	(0.003)	(0.005)	(0.008)	(0.008)
Log(CR past 6 months)	0.001	0.002	-0.002	0.009**	0.001	0.012**
	(0.002)	(0.003)	(0.002)	(0.004)	(0.005)	(0.005)
Outcome SD	1.015	1.069	0.958	1.383	1.364	1.403
R2	0.002	0.005	0.006	0.002	0.007	0.006
Observations	35,947,357	17,939,954	18,006,622	26,564,195	13,852,121	12,710,485

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)	-0.219***	-0.397***	-0.080	-1.299***	-2.762***	-0.318
	(0.057)	(0.137)	(0.091)	(0.133)	(0.196)	(0.215)
Log(CR past 1 week)	0.016	0.062**	-0.023	-0.184***	-0.348***	-0.035
	(0.016)	(0.027)	(0.027)	(0.018)	(0.031)	(0.022)
Log(CR past 1 month)	0.017***	0.015*	0.017	-0.011	-0.052***	0.019*
	(0.006)	(0.008)	(0.010)	(0.009)	(0.011)	(0.012)
Log(CR past 3 months)	-0.001	-0.004	0.001	0.013**	-0.002	0.030***
	(0.002)	(0.004)	(0.003)	(0.005)	(0.008)	(0.008)
Log(CR past 6 months)	0.001	0.002	-0.003	0.009**	0.002	0.012**
	(0.002)	(0.003)	(0.002)	(0.004)	(0.005)	(0.005)
Log(Ret Wealth)	0.571***	0.602***	0.531***	0.342***	0.345***	0.340***
	(0.023)	(0.024)	(0.041)	(0.015)	(0.019)	(0.018)
Log(Ret Net Inflows)	0.602***	0.629***	0.565***	0.363***	0.353***	0.369***
	(0.022)	(0.022)	(0.039)	(0.014)	(0.017)	(0.018)
Outcome SD	1.014	1.068	0.957	1.379	1.359	1.401
R2	0.003	0.007	0.007	0.002	0.008	0.007
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 change their trading behavior after the 2018 crypto crash. We focus on active investors, who traded any asset in the prior 7 days and who have been on eToro for at least 30 days, and have traded both cryptos and stocks during their tenure there. We generate a representative investor, by cumulating trades, net inflows, and wealth, across those investors for each date t. *After Crash* is an indicator variable equal to 1 if the date is after January 1, 2018 and 0 before. We exclude January and February 2018 from the analysis. 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. The log cumulative past returns are defined over a time period ending on day $t-1$. We interact all controls with the *After Crash* indicator. *Cryptos* are BTC, XRP, and ETH. For the list of the top 200 stocks by eToro trading, refer to Table A1. Standard errors are clustered at the date level and reported in parentheses. Statistical significance is denoted at the ten, five, and one percent levels by *, **, and ***, respectively.

Panel A

	Log(total share change)					
	Cryptos			Top 200 Stocks		
	All	Ret>0	Ret≤0	All	Ret>0	Ret≤0
	(1)	(2)	(3)	(4)	(5)	(6)
Log(Ret)	0.756***	0.869***	0.691***	-0.633***	-1.399***	-0.409
	(0.052)	(0.085)	(0.119)	(0.162)	(0.351)	(0.253)
After Crash	-0.003	-0.005	-0.007	-0.004	-0.009	-0.016**
	(0.006)	(0.008)	(0.009)	(0.004)	(0.007)	(0.007)
After Crash × Log(Ret)	-0.109	-0.093	-0.165	-0.063	0.502	-0.647*
	(0.077)	(0.094)	(0.130)	(0.210)	(0.400)	(0.383)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
R2	0.161	0.145	0.084	0.001	0.002	0.002
Observations	3,586	1,866	1,720	168,087	86,415	81,672

Panel B

	Log(active share change)					
	Cryptos			Top 200 Stocks		
	All	Ret>0	Ret≤0	All	Ret>0	Ret≤0
	(1)	(2)	(3)	(4)	(5)	(6)
Log(Ret)	-0.136**	-0.065	-0.219*	-1.566***	-2.343***	-1.379***
	(0.056)	(0.089)	(0.120)	(0.162)	(0.351)	(0.254)
After Crash	-0.008	-0.005	-0.015	-0.004	-0.017**	-0.012*
	(0.006)	(0.009)	(0.009)	(0.005)	(0.008)	(0.007)
After Crash × Log(Ret)	-0.157	-0.146	-0.139	-0.094	0.486	-0.715*
	(0.163)	(0.122)	(0.135)	(0.208)	(0.400)	(0.381)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
R2	0.151	0.151	0.166	0.009	0.007	0.011
Observations	3,586	1,866	1,720	168,087	86,415	81,672

Table 11. **Lottery-like Returns**

In this table we examine whether there is heterogeneity in how investors trade stocks based on whether the stocks exhibit lottery-like returns. We focus on investors who have traded both cryptos and stocks during their tenure at eToro. We generate a representative investor, by cumulating trades, net inflows, and wealth, across those investors for each date t. *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, plus the interactions of these returns with stock characteristics. The log cumulative past returns are defined over a time period ending on day $t-1$. For the list of the top 200 stocks by eToro trading, refer to Table A1. We follow definitions of lottery-like stocks from prior literature. *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 a firm that is less than a year old. *Gross Profitability* is revenues minus cost of goods sold divided by lagged total assets. 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)						
Log(Ret)	-0.696***	-1.576***	-1.001***	-1.591***	-2.542***	-1.898***
	(0.133)	(0.227)	(0.268)	(0.134)	(0.227)	(0.270)
Stock Characteristics	0.030	-0.088	0.059	0.018	-0.172***	0.108
	(0.037)	(0.057)	(0.066)	(0.040)	(0.062)	(0.069)
Stock Characteristics × Log(Ret)	2.139*	7.453***	2.043	1.920	7.632***	1.626
	(1.228)	(2.191)	(2.311)	(1.232)	(2.174)	(2.312)
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						
Log(Ret)	-0.359*	-1.608***	-0.491	-1.209***	-2.538***	-1.348***
	(0.189)	(0.308)	(0.401)	(0.192)	(0.308)	(0.406)
Stock Characteristics	-0.014	-0.382**	-0.097	-0.060	-0.440**	-0.159
	(0.119)	(0.173)	(0.223)	(0.116)	(0.173)	(0.238)
Stock Characteristics × Log(Ret)	-5.981	18.266***	-11.405	-7.902	17.647***	-13.478
	(4.922)	(6.881)	(10.658)	(4.969)	(6.833)	(10.730)
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						
Log(Ret)	-0.504***	-0.978***	-0.789***	-1.411***	-1.939***	-1.701***
	(0.096)	(0.195)	(0.173)	(0.096)	(0.194)	(0.175)
Stock Characteristics	-0.000	0.001	-0.002	-0.000	0.001	-0.003*
	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)	(0.002)
Stock Characteristics × Log(Ret)	-0.120***	-0.119	-0.155*	-0.133***	-0.127	-0.176**
	(0.045)	(0.092)	(0.087)	(0.045)	(0.093)	(0.087)
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						
Log(Ret)	-0.546***	-1.010***	-0.872***	-1.456***	-1.973***	-1.791***
	(0.097)	(0.192)	(0.181)	(0.097)	(0.192)	(0.183)
Stock Characteristics	0.012*	-0.002	0.032**	0.018*	0.007	0.035*
	(0.006)	(0.013)	(0.013)	(0.010)	(0.016)	(0.020)
Stock Characteristics × Log(Ret)	-0.117	0.191	0.388	-0.191	0.147	0.312
	(0.306)	(0.607)	(0.605)	(0.307)	(0.610)	(0.607)
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						
Log(Ret)	-0.476***	-0.842***	-0.759***	-1.382***	-1.792***	-1.680***
	(0.113)	(0.230)	(0.220)	(0.114)	(0.232)	(0.221)
Stock Characteristics	-0.002	0.008	-0.009	-0.003	0.006	-0.008
	(0.003)	(0.008)	(0.008)	(0.004)	(0.010)	(0.008)
Stock Characteristics × Log(Ret)	-0.209	-0.529	-0.329	-0.222	-0.568	-0.326
	(0.189)	(0.419)	(0.378)	(0.191)	(0.425)	(0.381)
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 change their trading behavior in stocks around earnings announcements. We focus on investors who have traded both cryptos and stocks during their tenure at eToro. We generate a representative investor, by cumulating trades, net inflows, and wealth, across those investors for each date t. *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. The log cumulative past returns are defined over a time period ending on day $t-1$. 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)					
	EA Days			Non EA Days		
	All	Ret>0	Ret≤0	All	Ret>0	Ret≤0
	(1)	(2)	(3)	(4)	(5)	(6)
Log(Ret)	-1.303***	-2.457***	-1.441***	-0.051	-0.287*	-0.106
	(0.215)	(0.391)	(0.396)	(0.082)	(0.164)	(0.164)
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)	-2.279***	-3.445***	-2.429***	-0.942***	-1.239***	-0.998***
	(0.215)	(0.391)	(0.395)	(0.081)	(0.163)	(0.159)
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 Stocks 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. **Gold - Low and High Leverage positions**

In this table we examine how contemporaneous and lagged returns affect individuals' trading behavior in gold for trades with low versus high leverage. We generate a representative investor, by cumulating trades, net inflows, and wealth, across all investors who had either low or high leverage in trades 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. The log cumulative past returns are defined over a time period ending on 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(($Wealth_t - NetInflows_t)/Wealth_{t-1}$). In Panel A, we examine trades with leverage of ≤ 20 , which make up 41% of trades, and in Panel B we examine trades with leverage of ≥ 50, which make up 51% of trades. 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: Leverage $\leq$ 20

	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)	-28.300***	-23.895***	-29.509***	-29.196***	-25.564***	-33.339***
	(2.918)	(2.873)	(4.616)	(2.927)	(3.415)	(5.525)
Log(CR past 1 week)	-0.774	-1.085	-0.604	-0.775	-1.145	-0.699
	(0.853)	(0.718)	(1.544)	(0.855)	(0.718)	(1.556)
Log(CR past 1 month)	0.561	0.024	0.758	0.560	0.027	0.764
	(0.368)	(0.439)	(0.580)	(0.369)	(0.441)	(0.582)
Log(CR past 3 months)	0.175	-0.529*	0.835*	0.167	-0.544*	0.843*
	(0.269)	(0.286)	(0.438)	(0.268)	(0.287)	(0.438)
Log(CR past 6 months)	-0.082	-0.439**	0.237	-0.078	-0.421**	0.223
	(0.190)	(0.174)	(0.351)	(0.190)	(0.177)	(0.350)
Log(Ret Wealth)				0.560	0.219	0.879
				(0.340)	(0.374)	(0.555)
Log(Ret Net Inflows)				0.752	0.878	-0.988
				(0.519)	(0.676)	(0.899)
R2	0.187	0.253	0.199	0.196	0.263	0.212
Observations	1,416	714	702	1,416	714	702

Panel B: Leverage $\geq$ 50

	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)	-45.724***	-56.102***	-36.076***	-46.721***	-55.405***	-33.485***
	(5.009)	(7.377)	(6.306)	(5.041)	(8.377)	(7.765)
Log(CR past 1 week)	4.453***	1.626	6.347***	4.404***	1.690	6.411***
	(1.569)	(2.201)	(2.134)	(1.577)	(2.204)	(2.154)
Log(CR past 1 month)	0.134	0.379	-0.350	0.099	0.313	-0.303
	(0.647)	(0.966)	(0.894)	(0.654)	(0.982)	(0.895)
Log(CR past 3 months)	0.062	-1.052	1.214**	0.067	-1.053	1.184**
	(0.461)	(0.688)	(0.588)	(0.461)	(0.688)	(0.586)
Log(CR past 6 months)	0.035	0.235	-0.070	0.038	0.228	-0.056
	(0.296)	(0.426)	(0.407)	(0.296)	(0.429)	(0.411)
Log(Ret Wealth)				0.351	0.932	-0.388
				(0.583)	(0.892)	(0.781)
Log(Ret Net Inflows)				-0.737	-0.144	1.703
				(1.357)	(2.247)	(2.328)
R2	0.169	0.209	0.157	0.175	0.213	0.164
Observations	1,277	628	649	1,277	628	649

Table A3. **Total and Active Share Change: Incorporating Leverage**

In this table we examine how contemporaneous and lagged returns affect individuals' trading behavior, while accounting for differences in leverage that different positions have. We generate a representative investor by cumulating trades, net inflows, and wealth, across all investors who participated on the platform at date t. When we cumulate shares that investors buy or sell, we multiply them by the amount of leverage that they take on in their positions. Shares owned$_t$ accounts for the fact that different shares had different amount of leverage. 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 cumulative past returns are defined over a time period ending on day $t-1$. Log(Ret Wealth$_t$) 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(($Wealth_t - NetInflows_t$)/$Wealth_{t-1}$). 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 trading on eToro 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)	0.682***	0.728***	0.638***	-0.008	0.005	-0.024
	(0.028)	(0.042)	(0.039)	(0.036)	(0.048)	(0.062)
Log(CR past 1 week)	0.016	0.030*	-0.001	0.018**	0.026*	0.008
	(0.010)	(0.016)	(0.009)	(0.008)	(0.014)	(0.008)
Log(CR past 1 month)	0.002	0.007	-0.004	0.001	0.002	-0.000
	(0.003)	(0.005)	(0.004)	(0.002)	(0.003)	(0.003)
Log(CR past 3 months)	-0.007**	-0.005	-0.010**	-0.008***	-0.005	-0.011**
	(0.003)	(0.004)	(0.004)	(0.003)	(0.003)	(0.004)
Log(CR past 6 months)	0.005***	0.001	0.008**	0.004**	0.000	0.008***
	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)
Log(Ret Wealth)				0.046	-0.005	0.116
				(0.051)	(0.070)	(0.075)
Log(Ret Net Inflows)				0.354***	0.398**	0.322*
				(0.113)	(0.160)	(0.175)
R2	0.268	0.307	0.227	0.017	0.017	0.025
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)	-0.644***	-0.783***	-0.553***	-1.580***	-1.797***	-1.624***
	(0.111)	(0.132)	(0.168)	(0.110)	(0.146)	(0.185)
Log(CR past 1 week)	-0.001	-0.079*	0.075*	-0.002	-0.085*	0.077*
	(0.032)	(0.046)	(0.042)	(0.032)	(0.045)	(0.043)
Log(CR past 1 month)	-0.008	-0.020	0.002	-0.012	-0.025	0.001
	(0.016)	(0.021)	(0.022)	(0.016)	(0.021)	(0.022)
Log(CR past 3 months)	0.015	0.018	0.011	0.014	0.018	0.010
	(0.011)	(0.016)	(0.015)	(0.011)	(0.016)	(0.015)
Log(CR past 6 months)	0.004	0.004	0.002	0.006	0.004	0.006
	(0.006)	(0.010)	(0.009)	(0.006)	(0.010)	(0.009)
Log(Ret Wealth)				0.275***	0.153**	0.366***
				(0.083)	(0.064)	(0.136)
Log(Ret Net Inflows)				0.260**	0.637***	-0.046
				(0.110)	(0.145)	(0.172)
R2	0.001	0.002	0.001	0.009	0.008	0.010
Observations	168,661	86,720	81,941	168,661	86,720	81,941

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)	-40.506***	-46.763***	-33.518***	-41.409***	-46.536***	-31.475***
	(4.430)	(6.821)	(5.679)	(4.462)	(7.507)	(6.861)
Log(CR past 1 week)	4.101***	4.090**	3.654**	4.097***	4.141**	3.736**
	(1.215)	(1.646)	(1.774)	(1.221)	(1.655)	(1.794)
Log(CR past 1 month)	0.159	-0.275	0.057	0.143	-0.326	0.087
	(0.541)	(0.804)	(0.787)	(0.549)	(0.812)	(0.792)
Log(CR past 3 months)	0.186	-0.997*	1.405**	0.186	-0.989*	1.377**
	(0.401)	(0.536)	(0.569)	(0.401)	(0.537)	(0.569)
Log(CR past 6 months)	-0.248	-0.566	0.037	-0.247	-0.581*	0.052
	(0.250)	(0.350)	(0.351)	(0.252)	(0.351)	(0.355)
Log(Ret Wealth)				0.455	1.010	-0.193
				(0.491)	(0.681)	(0.736)
Log(Ret Net Inflows)				0.120	0.216	1.596
				(1.053)	(1.433)	(1.850)
R2	0.184	0.264	0.159	0.189	0.270	0.167
Observations	1,276	627	649	1,276	627	649

Table A4. **Active Investors who Traded Today**

In this table we examine whether investors trade similarly when we define active as 'traded today.' We only look at investors who have traded in any asset on eToro on date t, have been on eToro for at least 30 days, and have traded both cryptos and stocks during their tenure there. We generate a representative investor, by cumulating trades, net inflows, and wealth, across those investors for each date t. 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. The log cumulative past returns are defined over a time period ending on day $t-1$. *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.

	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)	0.457***	0.758***	0.089	-1.097***	-0.826***	-2.040***
	(0.113)	(0.168)	(0.253)	(0.136)	(0.240)	(0.300)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
R2	0.004	0.011	0.003	0.001	0.000	0.003
Observations	3,467	1,789	1,678	162,765	83,655	79,110

	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)	-0.234	0.156	-0.264	-2.121***	-1.786***	-3.113***
	(0.197)	(0.193)	(0.182)	(0.133)	(0.240)	(0.296)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
R2	0.752	0.749	0.761	0.013	0.012	0.015
Observations	3,467	1,789	1,678	162,765	83,655	79,110

Table A5. **Active Investors with large Stock and Crypto Shares**

In this table we examine how active investors trade who have large shares of both cryptos and stocks (i.e., have skin in the game). An investor is defined as active if she traded any asset in the prior 7 days. We focus on investors who had at least 30% of their portfolio in stocks and at least 30% of their portfolio in cryptos, 7 days prior to 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. We generate a representative investor, by cumulating trades, net inflows, and wealth, across these investors for each date t. 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. The log cumulative past returns are defined over a time period ending on day $t-1$. *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.

	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)	0.615***	0.608***	0.604***	-0.181	-0.805**	0.044
	(0.050)	(0.092)	(0.093)	(0.183)	(0.360)	(0.310)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
R2	0.072	0.044	0.048	0.000	0.000	0.000
Observations	3,584	1,866	1,718	146,556	75,301	71,255

	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)	-0.153	-0.165	-0.155	-1.162***	-1.765***	-0.982***
	(0.149)	(0.193)	(0.0185)	(0.184)	(0.361)	(0.311)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
R2	0.344	0.288	0.417	0.005	0.004	0.007
Observations	3,584	1,866	1,718	146,556	75,301	71,255

Table A6. **Individual Investors - Non-logged Share Changes**

In this table we examine how contemporaneous and lagged returns affect individuals' trading behavior using account-level data. We only look at investors who have traded both cryptos and stocks during their tenure on eToro. We keep the top 50% of traders by the number of days they traded in stocks and cryptos on eToro. Total Share Change$_t$ is defined as Shares owned$_t$ $\times$ Price$_t$/Wealth$_t$ $-$ Shares owned$_{t-1}$ $\times$ Price$_{t-1}$/Wealth$_{t-1}$ and Active Share Change$_t$ is defined as (Shares owned$_t$ $-$ Shares owned$_{t-1}$) $\times$ Price$_{t-1}$/Wealth$_{t-1}$. 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. The log cumulative past returns are defined over a time period ending on day $t-1$. *Cryptos* are BTC, XRP, and ETH. For the list of the top 200 stocks by eToro trading, refer to Table A1. In Panel B Wealth Ret$_t$ is defined as $[Wealth_t - NetInflows_t]/Wealth_{t-1}$, and Ret Net Inflows is defined as $Wealth_t/Wealth_{t-1} - (Wealth_t - NetInflows_t)/Wealth_{t-1}$. All columns include individual, asset, 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

	Total share change x 100					
	Cryptos			Top 200 Stocks		
	All	Ret>0	Ret≤0	All	Ret>0	Ret≤0
	(1)	(2)	(3)	(4)	(5)	(6)
Ret	9.133***	7.474***	13.927***	-3.833***	-6.844***	-0.451
	(0.999)	(1.842)	(1.311)	(0.362)	(0.793)	(0.803)
CR past 1 week	-0.079	0.304	-0.231	-0.173**	-0.455***	0.116
	(0.183)	(0.238)	(0.330)	(0.068)	(0.102)	(0.096)
CR past 1 month	0.137***	0.090**	0.106	0.093***	0.085**	0.066
	(0.046)	(0.044)	(0.085)	(0.030)	(0.040)	(0.045)
CR past 3 months	-0.030	0.005	0.003	0.037**	0.053**	0.049
	(0.023)	(0.058)	(0.045)	(0.019)	(0.025)	(0.032)
CR past 6 months	0.003	-0.039	-0.004	0.021*	0.020	0.023
	(0.004)	(0.041)	(0.006)	(0.012)	(0.025)	(0.020)
Outcome Mean	-0.040	0.113	-0.198	-0.085	-0.143	-0.020
R2	0.000	0.001	0.002	0.000	0.002	0.004
Observations	56,788,880	28,856,423	27,932,198	76,098,653	39,839,701	36,257,855

Panel B

	Active share change x 100					
	Cryptos			Top 200 Stocks		
	All	Ret>0	Ret≤0	All	Ret>0	Ret≤0
	(1)	(2)	(3)	(4)	(5)	(6)
Ret	250.588	224.071	-705.020	-130.459**	17.324	-376.292**
	(161.987)	(180.109)	(950.582)	(57.439)	(32.069)	(184.441)
CR past 1 week	-146.455*	32.069	-365.246*	-4.676	1.772	-10.037
	(78.145)	(75.037)	(188.244)	(16.138)	(19.779)	(23.704)
CR past 1 month	24.577*	19.239	8.173	-8.003	-15.271	4.739
	(14.412)	(18.486)	(24.157)	(11.413)	(13.265)	(20.156)
CR past 3 months	11.826**	3.737	9.621	8.472	5.294	8.774
	(5.628)	(8.111)	(11.414)	(8.011)	(8.348)	(15.136)
CR past 6 months	2.189	3.452	1.781	-7.301	-4.950	-8.836
	(1.960)	(4.707)	(2.231)	(4.505)	(5.974)	(6.010)
Ret Wealth	12.705***	11.285***	15.847***	0.047	-0.050	0.163
	(3.503)	(3.181)	(6.067)	(0.604)	(0.494)	(0.754)
Ret Net Inflows	11.120***	8.544***	15.503***	0.238	0.094	0.406
	(3.015)	(3.139)	(5.546)	(0.554)	(0.463)	(0.682)
Outcome Mean	43.848	45.906	41.722	8.232	7.380	9.168
R2	0.154	0.168	0.167	0.003	0.003	0.007
Observations	56,831,151	28,878,138	27,952,754	76,166,504	39,873,885	36,291,529

Table A7. **Fee Removals**

In this table we examine whether the removal of trading fees for stocks in various countries has changed the way individuals trade in stocks. 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 generate a representative investor, by cumulating trades, net inflows, and wealth, across those investors for each date t. 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 April and May of 2019 (depending on the country). We exclude those two months from our analysis and compare the 'before period,' before April 2019 to the "After Fee" period, which is after May 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. We interact all controls with the *After Fee* indicator variable. The log cumulative past returns are defined over a time period ending on day $t-1$. For the list of the top 200 stocks by eToro trading, refer to Table A1. 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)	0.007	-0.165	-0.360***	-0.878***	-1.124***	-1.250***
	(0.086)	(0.202)	(0.135)	(0.088)	(0.204)	(0.137)
After Fee	0.002	-0.000	-0.004	-0.002	-0.009	-0.003
	(0.003)	(0.005)	(0.005)	(0.003)	(0.006)	(0.005)
After Fee × Log(Ret)	0.024	0.275	-0.223	-0.054	0.252	-0.300
	(0.142)	(0.278)	(0.274)	(0.145)	(0.279)	(0.281)
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 A8. **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. The log cumulative past returns are defined over a time period ending on 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 $\log(Wealth_t/Wealth_{t-1}) - \log((Wealth_t - NetInflows_t)/Wealth_{t-1})$. 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. We also control for the NASDAQ's cumulative index returns on day t. 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	ETH	XRP	BTC	ETH	XRP
	(1)	(2)	(3)	(4)	(5)	(6)
Log(Ret)	0.779***	0.702***	0.567***	-0.072*	0.126*	-0.084
	(0.045)	(0.043)	(0.038)	(0.042)	(0.066)	(0.064)
Log(CR past 1 week)	-0.002	0.030**	0.021	-0.000	0.025***	0.024**
	(0.018)	(0.013)	(0.014)	(0.015)	(0.010)	(0.012)
Log(CR past 1 month)	-0.000	0.003	-0.005	0.000	-0.000	-0.006*
	(0.009)	(0.003)	(0.004)	(0.007)	(0.002)	(0.003)
Log(CR past 3 months)	0.002	0.007***	-0.011***	0.003	0.005***	-0.012***
	(0.005)	(0.002)	(0.003)	(0.004)	(0.002)	(0.003)
Log(CR past 6 months)	-0.003	-0.005***	0.015***	-0.007**	-0.005***	0.013***
	(0.003)	(0.001)	(0.004)	(0.003)	(0.001)	(0.003)
Log(Ret Wealth)				0.106**	-0.159	0.118
				(0.047)	(0.103)	(0.120)
Log(Ret Net Inflows)				0.618***	0.188*	0.644***
				(0.182)	(0.113)	(0.143)
R2	0.220	0.530	0.444	0.018	0.076	0.177
Observations	1,708	1,020	858	1,708	1,020	858

Panel B: Stocks

	Log(total share change)			Log(active share change)		
	Tesla	Amazon	Apple	Tesla	Amazon	Apple
	(1)	(2)	(3)	(4)	(5)	(6)
Log(Ret)	0.012	0.308	-0.128	-0.906***	-0.465	-0.886***
	(0.166)	(0.372)	(0.219)	(0.164)	(0.388)	(0.221)
Log(CR past 1 week)	-0.120**	0.140*	-0.097	-0.118***	0.113	-0.137*
	(0.048)	(0.083)	(0.079)	(0.044)	(0.079)	(0.073)
Log(CR past 1 month)	0.024	0.032	-0.008	0.016	0.022	-0.005
	(0.023)	(0.061)	(0.033)	(0.022)	(0.059)	(0.032)
Log(CR past 3 months)	0.009	-0.001	0.014	-0.003	0.014	0.016
	(0.019)	(0.040)	(0.021)	(0.018)	(0.039)	(0.019)
Log(CR past 6 months)	-0.001	0.017	0.017	0.010	0.016	0.026
	(0.014)	(0.020)	(0.021)	(0.014)	(0.019)	(0.018)
Log(Ret Wealth)				0.070	0.125*	0.155**
				(0.065)	(0.070)	(0.072)
Log(Ret Net Inflows)				0.137	0.152	0.164
				(0.132)	(0.201)	(0.193)
R2	0.006	0.013	0.004	0.098	0.020	0.039
Observations	1,173	1,173	1,173	1,173	1,173	1,173

Table A9. **First trade in an Asset Class: Cryptos vs. Stocks**

In this table we examine how contemporaneous and lagged returns affect individuals' first trade in a given asset class. We only look at investors who have traded both cryptos and stocks during their tenure on eToro. 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. $Log(\text{Total Share Change}_t)$ 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 $\log(\text{Shares owned}_t) - \log(\text{Shares owned}_{t-1})$. $Log(Ret)$ is defined as log of return on day t plus 1. The log cumulative past returns are defined over a time period ending on day $t-1$. In Panel B $Log(\text{Wealth Ret}_t)$ is defined as $\log([Wealth_t - NetInflows_t]/Wealth_{t-1})$, and log(Ret Net Inflows) is defined as $\log(Wealth_t/Wealth_{t-1}) - \log((Wealth_t - NetInflows_t)/Wealth_{t-1})$. In Panel A, we examine cryptos, and in Panel B stocks. 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)	2.053***	4.162***	-0.365	1.131***	2.306***	0.289
	(0.407)	(0.524)	(0.816)	(0.391)	(0.590)	(0.921)
Log(CR past 1 week)	-0.272	-0.047	-0.507**	-0.332*	-0.064	-0.548**
	(0.170)	(0.236)	(0.226)	(0.172)	(0.234)	(0.228)
Log(CR past 1 month)	-0.015	0.036	-0.058	-0.039	0.030	-0.065
	(0.069)	(0.093)	(0.096)	(0.070)	(0.093)	(0.096)
Log(CR past 3 months)	0.021	-0.014	0.017	0.007	-0.020	0.010
	(0.042)	(0.052)	(0.063)	(0.042)	(0.052)	(0.063)
Log(CR past 6 months)	-0.007	-0.066**	-0.016	-0.042*	-0.077**	-0.031
	(0.023)	(0.029)	(0.033)	(0.024)	(0.031)	(0.033)
Log(Ret Wealth)				0.529	2.948***	-1.517
				(0.973)	(1.119)	(1.371)
Log(Ret Net Inflows)				6.301***	4.760**	3.653
				(1.508)	(2.004)	(2.383)
R2	0.010	0.041	0.005	0.011	0.033	0.008
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)	-2.435***	0.543	-3.013**	-2.158***	0.469	-4.121***
	(0.553)	(0.852)	(1.185)	(0.554)	(0.852)	(1.201)
Log(CR past 1 week)	0.015	0.482	-0.435	0.020	0.478	-0.416
	(0.245)	(0.337)	(0.337)	(0.245)	(0.337)	(0.337)
Log(CR past 1 month)	0.048	-0.343	0.453*	0.043	-0.343	0.435
	(0.186)	(0.240)	(0.266)	(0.186)	(0.240)	(0.266)
Log(CR past 3 months)	-0.073	0.163	-0.196	-0.073	0.166	-0.201
	(0.174)	(0.246)	(0.239)	(0.174)	(0.246)	(0.239)
Log(CR past 6 months)	0.068	0.138	0.047	0.068	0.134	0.059
	(0.109)	(0.159)	(0.160)	(0.109)	(0.159)	(0.160)
Log(NASDAQ Ret)	-0.309	-0.750	-0.590	0.129	-0.548	-0.253
	(1.904)	(2.646)	(2.618)	(1.971)	(2.669)	(2.781)
Log(NASDAQ CR past 1 week)	0.594	1.050	0.369	0.549	1.027	0.264
	(0.837)	(0.961)	(1.278)	(0.839)	(0.962)	(1.279)
Log(NASDAQ CR past 1 month)	-0.072	0.408	-0.272	-0.078	0.402	-0.304
	(0.471)	(0.597)	(0.663)	(0.470)	(0.596)	(0.660)
Log(NASDAQ CR past 3 months)	-0.186	-0.142	-0.495	-0.182	-0.150	-0.426
	(0.395)	(0.411)	(0.598)	(0.399)	(0.413)	(0.606)
Log(NASDAQ CR past 6 months)	-0.108	-0.367	-0.520	-0.110	-0.405	-0.371
	(0.222)	(0.257)	(0.346)	(0.236)	(0.273)	(0.360)
Log(Ret Wealth)				0.532	0.612	0.324
				(0.616)	(0.862)	(0.674)
Log(Ret Net Inflows)				0.698	1.248	-1.378
				(1.032)	(1.291)	(1.449)
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

Table A10. **Total 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 had non-leveraged trades 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. The log cumulative past returns are defined over a time period ending on 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(($Wealth_t - NetInflows_t)/Wealth_{t-1}$). 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)	0.669***	0.735***	0.591***	-0.017	0.010	-0.063
	(0.027)	(0.043)	(0.030)	(0.033)	(0.050)	(0.046)
Log(CR past 1 week)	0.023**	0.044***	-0.000	0.023**	0.038***	0.007
	(0.011)	(0.017)	(0.013)	(0.009)	(0.014)	(0.011)
Log(CR past 1 month)	0.002	0.007	-0.003	0.001	0.001	0.000
	(0.003)	(0.005)	(0.003)	(0.002)	(0.003)	(0.002)
Log(CR past 3 months)	-0.007**	-0.005	-0.010**	-0.008***	-0.005	-0.011***
	(0.003)	(0.004)	(0.004)	(0.003)	(0.003)	(0.004)
Log(CR past 6 months)	0.006***	0.002	0.008**	0.004*	-0.000	0.008**
	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)
Log(Ret Wealth)				0.028	-0.059	0.150**
				(0.049)	(0.067)	(0.063)
Log(Ret Net Inflows)				0.520***	0.512**	0.518***
				(0.129)	(0.207)	(0.171)
R2	0.303	0.354	0.244	0.036	0.040	0.046
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)	0.160***	0.349***	0.022	-0.761***	-0.569***	-0.964***
	(0.052)	(0.070)	(0.084)	(0.050)	(0.066)	(0.088)
Log(CR past 1 week)	-0.126***	-0.138***	-0.112***	-0.127***	-0.145***	-0.109***
	(0.018)	(0.027)	(0.023)	(0.017)	(0.025)	(0.021)
Log(CR past 1 month)	-0.012	-0.010	-0.013	-0.016**	-0.015	-0.016
	(0.009)	(0.012)	(0.011)	(0.008)	(0.011)	(0.011)
Log(CR past 3 months)	0.000	-0.001	0.003	-0.001	-0.001	0.001
	(0.007)	(0.009)	(0.009)	(0.006)	(0.008)	(0.008)
Log(CR past 6 months)	0.003	0.012*	-0.002	0.005	0.015**	-0.000
	(0.004)	(0.007)	(0.006)	(0.004)	(0.006)	(0.006)
Log(Ret Wealth)				0.108***	0.066*	0.146***
				(0.032)	(0.034)	(0.043)
Log(Ret Net Inflows)				0.276***	0.268***	0.050
				(0.057)	(0.072)	(0.076)
R2	0.002	0.003	0.001	0.009	0.005	0.016
Observations	169,151	87,050	82,101	169,151	87,050	82,101

Table A11. **Before versus After Crash: Investor Characteristics**

In this table we examine whether there is heterogeneity in how investors changed their trading after the crypto crash across investor characteristics. We only look at investors who have traded both cryptos and stocks during their tenure at eToro. We generate a representative investor, by cumulating trades, net inflows, and wealth, across those groups of investors for each date t. 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. We exclude January and February 2018 from the analysis. $Log(\text{Total Share Change}_t)$ 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. We interact all controls with the *After Crash* indicator. The log cumulative past returns are defined over a time period ending on day $t-1$. *Cryptos* are BTC, XRP, and ETH. For the list of the top 200 stocks by eToro trading, refer to Table A1. Standard errors are clustered at the date level and reported in parentheses. Statistical significance is denoted at the ten, five, and one percent levels by *, **, and ***, respectively.

Panel A

	Log(total share change)					
	Cryptos			Top 200 Stocks		
	All	Ret>0	Ret≤0	All	Ret>0	Ret≤0
	(1)	(2)	(3)	(4)	(5)	(6)
	Female					
After Crash × Investor Type × Log(Ret)	0.017	0.046	0.051	0.841	2.667**	-0.122
	(0.050)	(0.079)	(0.108)	(0.566)	(1.158)	(1.011)
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)	0.009	0.021	0.030	-0.626*	0.194	-1.141*
	(0.049)	(0.064)	(0.162)	(0.329)	(0.698)	(0.605)
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)	0.038	0.104	-0.075	0.392	1.242**	-0.119
	(0.050)	(0.068)	(0.155)	(0.263)	(0.541)	(0.415)
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)	0.042	0.025	0.096	0.282	0.309	0.059
	(0.040)	(0.058)	(0.084)	(0.263)	(0.639)	(0.392)
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)	0.342***	0.233***	0.350**	0.710*	1.632**	0.743
	(0.055)	(0.077)	(0.152)	(0.366)	(0.769)	(0.656)
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 (1)	Ret>0 (2)	Ret≤0 (3)	All (4)	Ret>0 (5)	Ret≤0 (6)
	Female					
After Crash × Investor Type × Log(Ret)	0.037	-0.023	0.183	0.884	2.684**	-0.081
	(0.067)	(0.101)	(0.154)	(0.572)	(1.157)	(1.016)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Outcome SD	0.087	0.090	0.083	0.834	0.873	0.791
R2	0.018	0.019	0.038	0.003	0.003	0.003
Observations	7,167	3,732	3,435	303,049	155,969	147,080
	Finance Background					
After Crash × Investor Type × Log(Ret)	-0.084	-0.057	-0.049	-0.664**	0.194	-1.164*
	(0.062)	(0.078)	(0.188)	(0.332)	(0.698)	(0.614)
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)	0.118*	0.160*	0.073	0.418	1.264**	-0.118
	(0.067)	(0.085)	(0.182)	(0.266)	(0.543)	(0.420)
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)	0.055	0.045	0.060	0.257	0.321	0.013
	(0.051)	(0.072)	(0.104)	(0.263)	(0.638)	(0.395)
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)	0.141*	0.054	0.144	0.716*	1.592**	0.799
	(0.073)	(0.085)	(0.210)	(0.370)	(0.773)	(0.661)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
R2	0.011	0.012	0.025	0.005	0.005	0.005
Observations	7,160	3,726	3,434	322,315	165,920	156,395

Table A12. **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 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. We generate a representative investor, by cumulating trades, net inflows, and wealth, across those investors for each date t. *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. 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)	-1.446***	-2.585***	-1.607***	-0.331***	-0.601***	-0.311
	(0.228)	(0.417)	(0.413)	(0.101)	(0.195)	(0.199)
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)	-2.431***	-3.576***	-2.607***	-1.240***	-1.560***	-1.234***
	(0.228)	(0.417)	(0.407)	(0.100)	(0.195)	(0.195)
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 A13. **Residualized Stock Returns and the Market Factor**

In this table we examine how investors react to individual stock returns residualized to the NASDAQ market factor and the NASDAQ market return separately. We generate a representative investor, by cumulating trades, net inflows, and wealth, across those investors for each date t. *Log*(Total Share Change$_t$) and *Log*(Active Share Change$_t$) are defined as in Table 3. *Resid. Log*(*Ret*) is defined as log of return on day t plus 1, residualized to log NASDAQ return on day t plus 1. *Resid. Log*(CR *past* 1 *week*) is defined as log of cumulative return over the past week ending on day $t-1$ plus 1, residualized to log of cumulative NASDAQ return over the past week ending on day $t-1$ plus 1. The rest of residualized returns are defined in a similar fashion. *Log*(Ret Wealth$_t$) is defined as $\log([Wealth_t - NetInflows_t]/Wealth_{t-1})$, and log(Ret Net Inflows) is defined as $\log(Wealth_t/Wealth_{t-1}) - \log((Wealth_t - NetInflows_t)/Wealth_{t-1})$. 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.

	Log(total share change)			Log(active share change)		
	All	Ret>0	Ret≤0	All	Ret>0	Ret≤0
	(1)	(2)	(3)	(4)	(5)	(6)
Resid. Log(Ret)	-0.472***	-0.456***	-0.566***	-1.463***	-1.469***	-1.597***
	(0.090)	(0.146)	(0.151)	(0.090)	(0.144)	(0.151)
Resid. Log(CR past 1 week)	-0.092***	-0.097**	-0.089***	-0.085***	-0.088**	-0.083***
	(0.024)	(0.039)	(0.030)	(0.024)	(0.039)	(0.030)
Resid. Log(CR past 1 month)	-0.027**	-0.039*	-0.015	-0.029**	-0.040**	-0.018
	(0.013)	(0.021)	(0.017)	(0.013)	(0.020)	(0.016)
Resid. Log(CR past 3 months)	0.009	0.025	-0.007	0.008	0.025	-0.010
	(0.013)	(0.022)	(0.013)	(0.013)	(0.022)	(0.013)
Resid. Log(CR past 6 months)	0.008	0.004	0.015**	0.010*	0.004	0.019***
	(0.006)	(0.008)	(0.007)	(0.005)	(0.008)	(0.007)
Log(NASDAQ Ret)	-0.467**	0.152	-0.686***	-0.895***	-0.298**	-1.198***
	(0.117)	(0.190)	(0.160)	(0.146)	(0.149)	(0.186)
Log(NASDAQ CR past 1 week)	-0.128***	-0.045	-0.344***	-0.187**	-0.115	-0.391***
	(0.059)	(0.096)	(0.083)	(0.076)	(0.074)	(0.094)
Log(NASDAQ CR past 1 month)	0.042	0.006	0.050	0.030	-0.001	0.032
	(0.033)	(0.043)	(0.041)	(0.026)	(0.037)	(0.036)
Log(NASDAQ CR past 3 months)	-0.040	-0.063**	-0.032	-0.017	-0.040	-0.012
	(0.025)	(0.031)	(0.032)	(0.018)	(0.026)	(0.024)
Log(NASDAQ CR past 6 months)	0.024	0.083***	-0.017	0.040***	0.081***	0.011
	(0.016)	(0.023)	(0.024)	(0.015)	(0.023)	(0.022)
Log(Ret Wealth)				0.076*	0.041	0.093
				(0.039)	(0.042)	(0.057)
Log(Ret Net Inflows)				0.052	0.300**	-0.148
				(0.098)	(0.125)	(0.135)
R2	0.002	0.001	0.004	0.011	0.008	0.016
Observations	170,878	87,894	82,984	170,878	87,894	82,984

Appendix B: Correlated Returns

In this section, we extend the result of Section 4 to accommodate the case of correlated returns within a given asset class. We assume that the returns follow a one-factor model:

$$\begin{aligned}
&r_{i,t} = a_{it} + \beta_i f_t + u_{it}, \\
&E_{t-1} f_t u_{it} = 0, \quad E_{t-1} u_{it} = 0, \quad E_{t-1} u_{it} u_{jt} = 0, \quad \text{for} \quad i \neq j, \\
&Var_{t-1}(f_t) = \sigma_f^2, \quad Var_{t-1}(u_{it}) = \sigma_{iu}^2.
\end{aligned} \tag{B1}$$

As before, the portfolio weights are given by

$$\mathbf{w_t} = \frac{1}{\gamma} \Sigma^{-1} (\mu_t - \mathbf{1} r_f + \sigma^2/2), \tag{B2}$$

and investors believe that the asset expected returns follow

$$\mu_{it} = \mu_i + \sum_{s=0}^{T} \alpha_s r_{i,t-s} + \varepsilon_{it}. \tag{B3}$$

PROPOSITION 1. *Suppose asset returns follow a one-factor model (B1), investors use portfolio policy (B2) and believe that the asset expected returns follow (B3). Then*

$$\frac{\partial w_{it}}{\partial u_{i,t-s}} = \alpha_s \Sigma_{ii}^{-1}, \tag{B4}$$

$$\frac{\partial w_{it}}{\partial f_{i,t-s}} = \alpha_s \Omega_i, \tag{B5}$$

where

$$\Sigma_{ii}^{-1} = \frac{\sigma_f^{-2} + \sum_{j \neq i} \beta_j^2 / \sigma_{ju}^2}{\sigma_{iu}^2 \left(\sigma_f^{-2} + \sum_j \beta_j^2 / \sigma_{ju}^2 \right)}, \tag{B6}$$

$$\Omega_i = \frac{\beta_i \sigma_f^{-2}}{\sigma_{iu}^2 \left(\sigma_f^{-2} + \sum_j \beta_j^2 / \sigma_{ju}^2 \right)}. \tag{B7}$$

Proof: The one-factor model implies that

$$\Sigma_{ij} = \begin{cases} \beta_i \beta_j \sigma_f^2, & \text{for} \quad i \neq j \\ \beta_i^2 \sigma_f^2 + \sigma_{iu}^2, & \text{for} \quad i = j. \end{cases} \tag{B8}$$

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

$$\Sigma = D + \mathbf{x}\mathbf{x}'. \tag{B9}$$

Using the Sherman–Morrison formula we have

$$\Sigma^{-1} = (D + \mathbf{x}\mathbf{x}')^{-1} = D^{-1} - \frac{D^{-1}\mathbf{x}\mathbf{x}'D^{-1}}{1 + \mathbf{x}'D^{-1}\mathbf{x}}. \tag{B10}$$

Direct computations show that

$$\Sigma_{ij}^{-1} = \begin{cases} -\frac{\beta_i \beta_j}{\sigma_{iu}^2 \sigma_{ju}^2 \left(\sigma_f^{-2} + \sum_j \beta_j^2/\sigma_{ju}^2\right)} < 0, & \text{for} \quad i \neq j \\ \frac{\sigma_f^{-2} + \sum_{j \neq i} \beta_j^2/\sigma_{ju}^2}{\sigma_{iu}^2 \left(\sigma_f^{-2} + \sum_j \beta_j^2/\sigma_{ju}^2\right)} > 0, & \text{for} \quad i = j. \end{cases} \tag{B11}$$

Therefore, we have

$$\frac{\partial w_{it}}{\partial u_{i,t-s}} = \frac{\partial w_{it}}{\partial \mu_{it}} \times \frac{\partial \mu_{it}}{\partial u_{i,t-s}} = \alpha_s \Sigma_{ii}^{-1} = \alpha_s \frac{\sigma_f^{-2} + \sum_{j \neq i} \beta_j^2/\sigma_{ju}^2}{\sigma_{iu}^2 \left(\sigma_f^{-2} + \sum_j \beta_j^2/\sigma_{ju}^2\right)}, \tag{B12}$$

$$\frac{\partial w_{it}}{\partial f_{i,t-s}} = \sum_j \frac{\partial w_{it}}{\partial \mu_{jt}} \times \frac{\partial \mu_{jt}}{\partial f_{i,t-s}} = \alpha_s \sum_j \beta_j \Sigma_{ij}^{-1} = \alpha_s \frac{\beta_i \sigma_f^{-2}}{\sigma_{iu}^2 \left(\sigma_f^{-2} + \sum_j \beta_j^2/\sigma_{ju}^2\right)}. \qquad Q.E.D. \tag{B13}$$

Equations (B4) and (B5) imply that

$$\begin{aligned} \frac{\partial(w_{it} - w_{it-1})}{\partial u_{i,t}} &= \alpha_0 \Sigma_{ii}^{-1} \\ \frac{\partial(w_{it} - w_{it-1})}{\partial u_{i,t-s}} &= (\alpha_s - \alpha_{s-1})\Sigma_{ii}^{-1}, \quad s = 1, .., T, \\ \frac{\partial(w_{it} - w_{it-1})}{\partial f_t} &= \alpha_0 \Omega_i, \\ \frac{\partial(w_{it} - w_{it-1})}{\partial f_{t-s}} &= (\alpha_s - \alpha_{s-1})\Omega_i, \quad s = 1, .., T. \end{aligned} \tag{B14}$$

The system of equations (B14) can be estimated using regression analysis by regressing the changes in the portfolio weights on the factor and residuals of returns.

In Appendix Table A13 we repeat our main analysis from Table 3, except we we first residualize individual stock returns to the NASDAQ return. We then regress the total and active share changes on the residualized stock returns and the NASDAQ return. Consistent with the model's predictions, the coefficients on the contemporaneous and 1-week lagged log residualized stock returns and the log

NASDAQ return are negative with a similar coefficient as in Table 3. This suggests that our main results go through even in the case that returns are correlated and follow a one-factor model.