Social media interactions and biases in investment decisions *

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Abstract This paper analyzes the interplay between social media interactions and well-established decision-making biases. We study investment decisions on a social trading platform and observe significant group differences: The manifestation of the house-money effect and the escalation of commitment differs between users that are being followed and those that are not. Trades with many followers are less likely to be closed and more likely to be increased. This is especially pronounced for trades with negative paper gains. We extend our findings to realized losses, contradicting the realization effect. Our results also suggest that advice seekers seem to be attracted by advisors susceptible to the disposition effect. Our paper has implications for both investment advisers and investors seeking investment advice.

Keywords: Investment advice, social trading, disposition effect, house-money effect, escalation of commitment, realization effect, Prospect Theory.

JEL Classification: G11; G23; G24; D14.

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Evidence from behavioral finance suggests that investors do not always behave consistently with the assumption of perfect rationality, as implied in modern portfolio theory (Statman et al., 2008), but are affected by many different psychological biases and emotions in their decision-making (Barberis and Thaler, 2003). Moreover, previous findings show that social interactions affect the behavior of investors. For example, Qin (2012) provide evidence that individuals have a tendency to observe other informed traders before making investment decisions. Regarding taking investment advice, Garcia (2013) states that individuals place greater weight on word-of-mouth communication than on professional advice. Moreover, Hong et al. (2004) show that social interactions alter the stock market participation of individual investors (Kaustia and Knüpfer, 2012, confirm this result), while Heimer (2016) presents evidence that social interaction increases behavioral biases such as the disposition effect and Ammann and Schaub (2016) find evidence that traders' communication affects the investment decisions of investors copying other users' strategies on an online trading platform. Most closely related to our paper, Liu et al. (2014) report that trades made in accordance with others' suggestions are more likely to be winning trades than are those detached from social interaction. Applying these insights to social trading suggests that investors exposed to social interactions and non-social traders should differ in the intensity with which they exhibit psychological biases.

The present digital era is poised to revolutionize financial intermediation. Previously, households wanting to invest in financial markets had to commission financial intermediaries to execute their trades. Today, an innovative combination of social networks and online trading, so-called social trading platforms, allows users to buy and sell securities with very low barriers to entry. In addition, these platforms allow users to interact with one another and view other investors' trading activities, e.g., investments in a given stock and the profits made. Investors can study and replicate others' trading strategies without the aid of a professional broker who assists them in making informed trading decisions. As a consequence of the increased attention paid to social trading platforms, established investment banks such as Goldman Sachs have invested in social trading platforms (Motif Investing), and the U.S. Securities and Exchange Commission (The Securities and Exchange Commission, 2012) and other supervisory authorities have taken notice of their business model.[1]

A commonly used feature of many of these platforms is the ability to manually (copy trading) or automatically (mirror trading) copy the strategies of other traders. We label these social trades. Although traders exploiting these possibilities do not directly pay a commission to the investors they duplicate, manual copy trading can be described as a form of investment advisory and mirror trading as a form of delegating the management of a portfolio (Doering et al., 2015).[2] In this regard, social trading platforms are potential substitutes for common asset management services and can facilitate access to financial markets for individuals outside the financial sector.

In this paper, we study the influence of social interaction in the context of investment decisions and risk-taking. We use the copy feature of social trading platforms to categorize their users. We differentiate among users who (i) execute trades on their own without engaging in social interaction (single traders), (ii) manually duplicate the investment strategies of other traders (copy traders), (iii) automatically duplicate the investment

[1]See, e.g., "Social trading regulation benefits for traders?", Forex crunch, July 11, 2016; "Social trading targets savvy retail investors", Financial Times, June 22, 2013; "UK's financial regulator warns on copy trading", Financial Times, March 10, 2015.

[2]Investors whose strategies are copied receive a payment for sharing their trading strategies. The amount of money received varies with the number of users copying their strategy, the platform, and the success of their strategies.

strategy of one or more selected investors (mirror traders), and (iv) have their investment strategies copied by other users (leader traders).[3] Then, we investigate whether investment behavior differs significantly across these trader types. Does the trading behavior of social investors (i.e., those who copy or mirror other investors) and non-social investors (i.e., those who do not copy other investors) differ? In what regard do leader and single traders differ? Do leader traders attract followers because they are less susceptible to psychological biases? Are leader traders more successful in their investment decisions because they are less susceptible to psychological biases?

We exploit large-scale financial transaction data from the world's leading social investment platform *eToro* (*www.etoro.com*) to study the underlying rationales and psychological biases of investors. We focus on risk-taking after previous losses and gains and study the house-money effect (Thaler and Johnson, 1990), the escalation of commitment (Staw, 1976; Shefrin and Statman, 1985; Odean, 1998), and the realization effect (Imas, 2016). We investigate whether investors on the platform exhibit behavior consistent with one of these biases after previous losses or gains. Additionally, we study the closely related disposition effect, whereby investors are reluctant to close losing positions. It describes investors' tendency to sell an asset when its price has increased but keep it when it has declined in value.

One aspect of particular interest is the traders' choice of who to follow and when. Finding an appropriate trader to follow on the platform is certainly not an easy task. Because traders can freely choose who to follow, it is not necessarily the case that leaders are more sophisticated or experienced or that their performance is better than that of other traders. Even following investors with a *sound* track record does not necessarily ensure good future

[3]Note that the trades executed by leaders can themselves be copied or mirrored by other users. However, this paper classifies all trades that are being followed as leader trades.

performance (See, e.g., Barber and Odean, 2000; Busse et al., 2010, for empirical evidence that neither individual nor professional investors are able to consistently outperform the market over long time periods.).

Exploiting a dataset containing approximately 26.5 million trading observations from 79,922 unique traders for the period from January 2012 to December 2012, we find clear evidence that investment behavior differs across different trader types and between winning and losing traders. While single traders' willingness to increase an existing position decreases with the profit of the trade, i.e., the traders exhibit behavior consistent with the escalation of commitment, the reverse is true for leader traders. Leader traders' behavior is more consistent with the house-money effect. Interestingly, mirror traders seem particularly prone to copy those traders who exhibit weaker evidence of the house-money effect. While all trader groups show evidence of the disposition effect, the degree to which they do so differs. We also find evidence that social investors are more likely to follow users that a very susceptible to the disposition effect. In the economic literature, the most common explanation for the the analyzed behavioral biases refers to Prospect Theory (Kahneman and Tversky, 1979; Tversky and Kahneman, 1992). Prospect Theory studies decision-making under risk and assumes that individuals evaluate outcomes relative to a reference point. In the context of investment decisions, a security's purchase price can be seen as such a reference point. As a consequence, decisions are based on potential gains and losses instead of final outcomes. The resulting value function is assumed to be concave for gains (i.e., individuals exhibit risk-averse behavior) and convex for losses (i.e. individuals exhibit risk-seeking behavior) and steeper for losses than for gains. Accordingly, losses have greater value (i.e., emotional impact) than equivalent gains.

In terms of the disposition effect, winnings are realized at the concave part of the value function, and as a consequence, investors prefer to reduce a risky position to realize a certain gain. In contrast, losses shift investors to the convex part of the value function, increasing their willingness to hold a losing position for longer, in hope of reducing the loss. This has been termed the reflection effect. Although Prospect Theory is often recognized as an explanation for the disposition effect (see, e.g., Shefrin and Statman, 1985; Odean, 1998; Weber and Camerer, 1998; Grinblatt and Keloharju, 2001), other explanations include realization preferences (Barberis and Xiong, 2012; Ingersoll and Jin, 2013), cognitive dissonance (Chang et al., 2016), pseudo-rational behavior (Odean, 1998), adverse selection (Linnainmaa, 2010) and mean-reverting beliefs (Odean, 1998).

Our paper contributes to the literature studying households' investment behavior. Odean (1998) is the first to study investors' trading behavior in the stock market. He studies the investments of 10,000 accounts in a U.S. discount brokerage from 1987 through 1993. His quantitative method provides evidence for the disposition effect by analyzing the frequency with which investors sell winning and losing trades relative to the corresponding gain or loss opportunities. He finds that the proportion of realized winning trades is significantly higher than the proportion of losing trades, except in the month of December. Since then, several empirical studies have found similar results for different time periods and data sets (Grinblatt and Keloharju, 2001; Da Costa et al., 2013) and in laboratory experiments (Weber and Camerer, 1998; Chui, 2001; Weber et al., 2007; Rubaltelli et al., 2005).

Moreover, our work contributes to the recent literature on social media and capital markets in general and on social trading platforms in particular. Social media allows for the collection of large-scale detailed data on behavior and decision-making at the aggregate level of society. Thus, unsurprisingly, a large body of literature focuses on the interaction between social media and stock markets. Most of that literature focuses on well-known social media platforms such as Facebook (Siganos et al., 2014; Karabulut, 2013) or Twitter (Bollen et al., 2011; Sprenger et al., 2014a,b), while other contributions exploit social networks that specialize in financial markets, such as StockTwits (Wang et al., 2015), Seeking Alpha (Chen et al., 2014; Wang et al., 2015), Sharewise (Pelster and Breitmayer, 2016), or eToro (Pan et al., 2012; Liu et al., 2014). In this new strand of literature, Doering et al. (2015) discuss institutional aspects of social trading platforms. The authors argue that such platforms reduce information asymmetries between investors and portfolio managers. Pan et al. (2012) study the roles of social mechanisms by analyzing daily trades. They find that social trading improves the likelihood of a winning trade. However, they also report that each trade lost an average of approximately 2.8% of its position size. Oehler et al. (2016) examine the performance of wikifolio certificates between 2012 and 2013. On average, wikifolios do not outperform the market. Chen et al. (2014) analyze the role of social media in financial markets, focusing on the extent to which published articles on Seeking Alpha predict future stock returns and earnings.[4] Similarly, Wang et al. (2015) investigate the quality and impact of information exchanged on the platforms SeekingAlpha and StockTwits and find a low correlation between the information exchanged and aggregate stock performance. Most recently, Pelster and Breitmayer (2016) find that crowd stock assessments, released on the social trading platform Sharewise, effectively explain stock returns.

[4] Chen et al. (2014) also introduce three possible reasons that informed users could have incentives to share their insights with other users. This includes an increase in utility due to the attention and recognition received on the platform, the financial compensation from assessments that ended in a profitable result, and the convergence of market prices to the true values perceived by the authors, as a consequence of the information exchanged on such platforms.

1 Data

The empirical analysis is based on individual investors' transaction data from the online social trading platform *eToro*. As of this writing, *eToro* has approximately 4.5 million registered users (according to the website). The platform allows its users to trade contracts for difference (CFD) that cover currency pairs, stocks, commodities and indices by taking short and long positions. Users can start their trading activity after paying a minimum deposit amount, which varies between $50 and $300 based on a user's region, and leverage trades up to 400 times. One of the most prominent features is the option to trade open to the public − also known as *Open Book* − which means that investors can access other investors' trading information. The information includes the investor's trading history, risk levels, returns and performance.

eToro allows its users to trade passively, meaning that other investors' trades are automatically copied, so-called *mirror trading*. The mirror trading mechanism allows users to select any amount of traders to be copied. Followed traders are copied proportionally, meaning that if the followed trader risks 1% of her equity on a specific trade, then *eToro* will use exactly 1% of the user's allocated equity to mirror that trade. Users can allocate up to 40% of their equity to mirror any trader. Additionally, a user can manually copy trades by other users executed on the platform with the click of a mouse. *eToro* provides users with additional compensation for being followed.

Our dataset consists of all trades executed on the *eToro* platform between January 1, 2012, and December 31, 2012. In total, approximately 26.5 million trades were executed during that period by 79,922 traders. Regarding the different trade types, approximately 19% are single, 1.5% are leading, 77.7% are mirror, and 1.4% are copy trades. In 2012, users engaged in trading activity through 32 instruments. Among the instruments traded most heavily are the EUR/US foreign exchange rate, representing approximately 37% of all transactions, the GBP/USD foreign exchange rate, representing approximately 14% of all transactions, and the AUD/USD foreign exchange rate, representing approximately 13% of all transactions. Furthermore, gold is traded heavily and constitutes approximately 7% of all trades. In addition to FX and commodities, several indexes, and some single name stocks are traded. The most commonly traded single name asset is the Apple stock listed on Nasdaq.

2 Analysis of trading behavior

2.1 Social and non-social trade type performance

We begin our analysis by presenting several descriptive statistics analyzing the performance and trading behavior of the different trade types. Panel (a) of Figure 1 displays the fractions of winning trades ($N_+/N_+ + N_-$) for the four trade types. We observe that the dataset contains significantly more winning than losing trades. Moreover, we find that the fraction of winning trades is highest for mirror trades (consistent with Pan et al., 2012; Liu et al., 2014) and lowest for single trades. The fraction of winning trades for leader trades is lower than that for mirror traders, which has two potential explanations. First, followers may alter a position on their own after they are engaged in it. They may close the position earlier or unfollow the leader and hold the position longer. Second, followers may particularly prefer a specific segment of leader traders. Hence, this part of the leader group is assigned a greater weight (as they have more followers). Our results suggest the intuition that leaders with a higher winning percentage are followed more often, which is reflected by the higher winning percentage of mirror trades. Hence, most followers seem to be able select the *right* users to follow. In other words, followers seem to be able to specifically identify users to follow that have a high ratio of winning trades. This observation is in line with the findings of Pan et al. (2012) and Liu et al. (2014), who report that social trades are more likely to be winners than are non-social trades, particularly when considering the relative frequency of the corresponding trade type.

- Place Figure 1 about here -

When considering the returns on investments (ROIs), the situation is quite different (Panel (b) of Figure 1). On average, and across all groups, ROI is negative. Differences between groups are minor, except for the mirror group, which exhibits significantly higher ROIs. The graphical illustration is confirmed by a simple t-test ($p < 0.01$). Thus, although the fraction of profitable trades is higher than of non-profitable trades, this does not necessarily lead to higher ROIs. To explain this, we separately study the ROIs of profitable (Figure 1, Panel (c)) and unprofitable positions (Figure 1, Panel (d)). Here, we again find significant group differences. Mirror trades on average generate significantly ($p < 0.01$) less profitable ROIs than the other three trade types, while profitable copy trades exhibit the highest ROI. Similar to non-profitable trades, mirror trades generate significantly lower ROIs on average than single and leading trades. For losing trades, single trades show the best ROI. Thus, although the likelihood of generating profitable trades is comparably high for all groups, their ROIs are, on average, not high enough to offset the losses from unprofitable trades. Overall, single trades significantly outperform ($p < 0.01$) social trades (mirror and copy trades), despite being less likely to realize a profitable trade. This is because the average ROI of profitable and unprofitable single trades is significantly higher than those of social trade types. Although mirror trades have are the most likely to realize a profitable trade, the average ROI is smaller than that of single trade types. In summary, social trading does not significantly improve the performance of investors.

To provide further insights into the observed performance on the social trading platform, we calculate several behavioral ratios introduced by Liu et al. (2014). First, we calculate the winning percentage ($w = N_+/(N_+ + N_-)$), which measures the share of positive trades, N_+, to total trades, $N_+ + N_-$, for each trader. A ratio of w higher than one-half means that traders make, on average, more positive than negative trades. Figure 2 illustrates the winning percentage distribution, $P(w)$, which is clearly asymmetrically distributed around one-half. Approximately 85% of the w values have a value greater than one-half, meaning that most investors have a higher share of positive trades. Most mass can be observed between 0.75 and 0.9. The winning percentage distributions for winning and losing traders are significantly different from one another ($p<0.01$) according to a Wilcoxon-Mann-Whitney test. While it is not surprising that most winning traders have a higher share of positive trades, the smaller but still large share of losing traders with more positive than negative trades is worth mentioning.

- Place Figure 2 about here -

Next, we estimate the win-loss ROI ratio ($u = ROI_+/ROI_-$), which is the ratio between positive and negative ROIs (Liu et al., 2014). ROI_+ and ROI_- are the average ROIs of positive and negative trades for each trader. A u ratio higher than one implies that traders have, on average, a higher ROI for positive than for negative trades. The win-loss ROI ratio distribution, P(u), is illustrated in Figure 3. The graphs display an exponential decrease in u converging to 0. P(u) has a high peak for u ratios between 0 and 0.2, which account for approximately 45% of all u values. Approximately 90% of the traders' u

ratios can be found below the threshold $u = 1$. This confirms our previous findings that most traders realize negative returns on average: Small profitable positions can be easily canceled out by large losses.

- Place Figure 3 about here -

2.2 Security holding time

Turning to trading behavior, we discuss the average holding time of securities. The holding time, t, is defined as the difference between a position's closing and opening time in milliseconds ($t = t_{closed} - t_{opened}$). Holding time distributions for positive and negative trades are calculated separately, based on their ROI. Positions exactly breaking even are excluded. The holding time distribution of all positions (Figure 4) shows that more than half of all positions are held no longer than one day. Only approximately 5% of all trades are held for longer than one month. This highlights that the network constitutes a trading rather than an investment platform.

- Place Figure 4 about here -

We observe that the holding time distributions of positive and negative trades are significantly different from one another. The graphical results are confirmed by the Wilcoxon-Mann-Whitney test ($p < 0.01$). On average, positive trades are held for a shorter time period (except for holding times of less than one minute) than negative trades. Turning to the analysis of group differences, we present the holding time distributions of positive and negative trades for different trade types in Figure 5.

- Place Figure 5 about here -

From single through leader to mirror trades, the likelihood that positive trades have a significant shorter holding time than negative trades increases significantly. Overall, there is a clear pattern that shorter time periods are disproportionately populated by trades with a positive ROI, while the inverse is true for longer time periods. A possible explanation is the individual's desire to promptly realize gains while holding onto losses in the hope that the market will move in her favor. The observation that negative trades are held much longer than positive trades is extremely pronounced among the mirror trades.

Although mirror trades automatically copy leading trades, their holding time distribution patterns for both positive and negative trades are not similar to one another. The same holds for copy trades. The explanations presented in the previous section also apply here: Some leader traders are mirror or copied more often than others, which places greater weight on their decisions, or some mirror or copy trades may be closed manually by the user holding the position. This would be the case when the user decides to no longer follow the given leader. In particular, the probability of holding negative trades is much higher for longer time intervals. These differences between the holding time distributions of social trades compared with leading trades support our previous findings concerning the returns of trades. Although mirror trades automatically copy leading trades, the variations between the distributions of mirror and leading trade types can result from a higher proportion of leading trade types being followed that hold losing trades longer (in other words, that are more prone to the disposition effect).

To shed further light on this issue, we calculate the win-loss holding time ratio ($s = t_+ / t_-$), defined as the ratio of the average holding times for positive, t_+, and negative trades, t_-, for each trader. On average, a ratio s higher than one implies that a trader holds positive trades longer than negative trades. Note that if traders do not exhibit a tendency to hold losing positions longer than winning positions, the distributions of the ratio should be symmetric around one.[5]

Panel (a) of Figure 6 shows the win-loss holding time distribution, $P(s)$, for all traders. The graph shows an asymmetric distribution with a peak at values between 0.1 and 0.2. As s increases, the function decays exponentially and converges to zero. Panel (b) of Figure 6 shows the win-loss holding time distributions for winning and losing traders. While both figures show similar patterns, there are significant differences between the distributions (Wilcoxon-Mann-Whitney test with a p-value smaller than 0.01). Ratios lower than one are more frequent for losing traders than for winning traders. While fewer than 5% of losing traders exhibit a ratio s larger than three, more than 20% of winning traders do so. Both winning and losing traders are prone to hold negative trades longer than positive trades, on average. This result provides evidence that winning traders are less prone to the disposition effect and indicates that this behavioral tendency may negatively affect market investment performance.

- Place Figure 6 about here -

Next, we plot holding time durations as a function of ROI. Figure 7 shows the box-and-whisker plots for the duration times binned logarithmically ($\log(t)$) depending on the corresponding ROIs for all trades. As can be seen in the figure, holding time medians of positive and negative ROIs are distributed asymmetrical around zero. Medians for positive positions are predominantly lower than those of equivalent negative positions. This implies that investors tend to close profitable positions earlier than unprofitable

[5]This assumes that the probability of a positive (negative) trade is one-half (one-half) and distributed symmetrically for positive and negative trades and their corresponding holding time. Although this is obviously not the case, the value of one nonetheless serves as a helpful benchmark.

positions of the same magnitude. Such behavior is consistent with the disposition effect and can be explained by loss aversion and the reflection effect (see Kahneman and Tversky, 1979; Tversky and Kahneman, 1992). Investors are more willing to close a profitable position and realize a profit. However, in the case of an unprofitable position, investors seem reluctant to realize losses and instead hold onto the position.

- Place Figure 7 about here -

To shed light on the group differences, we display the holding time as a function of ROI for the four different trade types in Figure 8. The differences in the holding time medians across ROIs among the four trade types show the variations in the sensitivity of different investors to losses and gains of the same magnitude. The figure suggests significant group differences, especially when copy trades are compared to non-social trades. For copy trades, the holding time distribution is almost symmetric. If anything, the holding times for trades with a positive ROI are slightly larger than those for trades with a negative ROI.

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2.3 Probability of closing positions

Building on our descriptive analysis, we next model the determinants of the probability of closing existing positions. As indicated by our descriptive observations, we expect (i) that winning positions are significantly more likely to be closed and (ii) that the probability of closing winning positions differs significantly between social and non-social trades as well as for leader trades.

To analyze the probability of closing an existing position, we employ a probit regression model. In this analysis, we include all positions that were opened and closed on different trading days.[6] Our dependent variable is a dummy variable taking value one on the day when a position is closed and zero otherwise. Our main independent variable is a dummy variable that takes value one when the position exhibits positive paper profits. Paper profits capture current (not realized) gains and losses. To determine whether the position is winning or losing, we compare the purchase price with the closing price of each given day. We split our dependent variable in four distinct variables, one for each trade group. For example, the variable *Profitable trade*, *single trades* takes value one if the position currently exhibits positive paper profits and is a single trade, zero otherwise. We employ the separate variables to study differences across trade groups. Our second variable of interest is the number of followers (*Followers*). Naturally, this variable is particularly interesting for leader trades and takes value zero for other trade types. As control variables, we include a dummy for the trade group (single trades are the baseline) and a dummy variable that captures whether the position is a long or short position (*Long*). Moreover, we include month dummies to control for unobserved heterogeneity in overall trading behavior. Table 1 presents the models to analyze the investors' propensity to close winning positions sooner than losing positions. The table presents marginal effects with standard errors clustered at the user level.

- Place Table 1 about here -

First, we observe that profitable trades are more likely to be closed. This result holds equally for all trade groups and is consistent with the disposition effect. For single trades, the probability that the position is closed on a given trading day increases by 14.5% if the position is currently profitable. This result is even more pronounced for leader trades (20.4%). For mirror trades, this effect is the most pronounced. Here, the probability of

[6] As some users in our sample never open and close a position on different trading days, the remainder of our analysis is limited to 75,832 users.

closing an existing position increases by 25.4% if the position is profitable. In a more detailed examination of the social interaction, we observe that the probability of closing an existing position decreases with the number of followers. The variable $Followers$ enters Model 2 with a negative sign but a small value. The probability of closing a position decreases with the number of followers. This relationship is illustrated in Figure 9. The figure shows that the likelihood of closing a position decreases in the number of followers.

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In Models 3-5, we replace our dummy variables denoting profitable trades with a continuous variable capturing the current paper gains of an existing position. The continuous variable $Profit$ not only captures the effect of profitable positions on the probability of closing a position but also allows us to analyze the effect depending on the size of a position's gains or losses. The continuous variable confirms our findings. In Model 5, we restrict our sample to leader trades to further investigate the influence of $Followers$ on the probability of closing an existing position. We hypothesize that the influence of followers on the propensity to close a position differs between winning and losing trades. We split the variable $Followers$ by $Profitable\ trade$ and confirm our hypothesis. For losing trades, the marginal effect on the probability of closing a position amounts to a negative 12.7%. The holding time of a security is shorter (i.e., a position is more likely to be closed) for profitable trades compared to unprofitable trades when the number of followers increases. By maintaining a losing position, the leader does not admit to have made an incorrect investment decision. Admitting one's fault is especially painful when a large group of investors follows one's trading strategy.

Investor characteristics represent one possible explanation for the observed group differences. Although the dataset does not allow us to directly control for investor characteristics, copy traders could be more experienced than mirror traders. Previous studies on investor biases show that investors who trade more frequently and are more experienced are less affected by biases such as the disposition effect (see, e.g., Da Costa et al., 2013). Copy trade types are the least prone to the disposition effect. In contrast to the mirror trade type, copy trade types manually select each trade that they wish to copy and could have more updated and precise knowledge on how each (copied) trade performs. Perhaps even more important, the discomfort when facing unprofitable trades might be lower when poor performance can be attributed to the decisions of someone else, in this case the investor whose trade was copied. In line with the theory on cognitive dissonance (e.g., Festinger, 1962), admitting the errors of others is easier than admitting one's own mistakes. Cutting losses is thus less painful when the decision to buy the security is attributed to the decision of another investor (e.g., Chang et al., 2016). However, considering both mirror and copy trades, we do not find evidence that social trade types are less prone to the disposition effect than non-social trade types. On the contrary, especially mirror traders seem to be highly susceptible to such bias. This is very likely induced by the selection of leader traders, e.g., by the number of followers differing from one leader to the next. We argue that the disposition effect is stronger for mirror trade types than for leading trade types because, on average, mirror trade types more often follow leading trade types with a higher disposition effect. One possible explanation for why leading trade types with a higher disposition effect are followed more often is the compensation the leading type users receive from the platform for each follower. Generating frequent profitable positions, i.e., closing profitable positions sooner to take a small profit or ROI, signals "good performance" to (potential) followers. Closing negative positions not only deteriorates one's overall performance but can also deter (potential) followers. A decrease in the number of followers reduces the compensation that investors who are followed receive from the trading platform.[7]

2.4 Probability of increasing existing positions

In our next step, we turn to the question of whether users' propensity to increase a position (i.e., purchase (sell) additional assets when they already have a long (short) postion of the same asset in their portfolio) differs for winner and loser assets. In an extension of the disposition effect, Odean (1998) find that investors purchase additional shares of stocks with a paper loss relatively more often than shares of stocks with a paper gain. The authors argue that decreased risk aversion after a loss and increased risk aversion after a gain is responsible for this behavior. Decreased risk aversion after a loss was first documented by Thaler and Johnson (1990), who label their observation the break-even effect. People are willing to take on more risk to break even. In the psychological literature, this type of behavior is also well documented under the term escalation of commitment (Staw, 1997). Brockner (1992) explains this behavior with the value function from Prospect Theory. Following a paper loss, investors are in the convex region of the value function and accordingly increase their risk taking, as subsequent losses hurt relatively less, but any subsequent gain feels particularly good. A different explanation for escalation of commitment is the self-justification hypothesis proposed by Staw (1976). He argues that individuals maintain a course of action because they feel the need to justify their initial decisions. Consistent with self-justification, investors could perceive a price decrease as a good buying opportunity (Weber and Camerer, 1998). It

[7] Monetary compensation is not necessarily required for this behavior. Users might wish to be followed because of intrinsic motivations (see, e.g., Frey, 1994).

should be noted that rationales for the escalation of commitment do not exclusively come from the behavioral perspective. Similarly, prior gains and losses can affect risky choices under expected utility maximization, as the outcomes change current wealth. Thus, increasing relative risk aversion yields escalation of commitment. Moreover, an investor optimizing her portfolio weights would have to rebalance her portfolio to keep the weights constant after a loss.

However, investors may purchase additional assets with a paper gain relatively more often than assets with a paper loss. This behavior would indicate decreasing risk aversion following a gain. Evidence of this behavior, labeled the house-money effect, is provided by Thaler and Johnson (1990). Weber and Zuchel (2005) study both the house-money effect and escalation of commitment in an experimental setting and show that for content-related equivalent decision problems, the framing of the decision problem determines the behavior of participants. When the problem is presented as a portfolio problem, the authors find evidence consistent with escalation of commitment, that is, decreasing risk aversion following losses. Conversely, when the problem is presented as a two-stage lottery, the authors demonstrate that participants' behavior shows greater risk-taking following gains, which is consistent with the house-money effect. To date, there is no evidence on how the social interaction on a social trading platform may influence investor behavior. However, with respect to the results of Weber and Zuchel (2005), we expect to observe evidence consistent with escalation of commitment for the behavior of investors. In other words, we expect users to be more likely increase their positions following a loss than following a gain.

We begin our analysis on the probability of increasing positions by presenting descriptive statistics. Figure 10 shows the fraction of increased positions by trade groups. Panel (a) shows all traders. The figure shows that across all trade groups, non-profitable trades are increased more often than are profitable trades. Yet, across all trade groups, approximately 20% of profitable trades are also increased. The figure also displays significant group differences (confirmed by t-tests). Notably, profitable trades are significantly more likely to be increased when the trade is copied or mirrored by other investors. Moreover, social trades exhibit the highest fraction of increased trades. Possibly, investors observe that the assumed trading strategy is profitable and consequently increase their position. Another possible explanation is that leaders that exhibit a higher propensity to increase profitable positions have more followers.

- Place Figure 10 about here -

Panel (b) [(c)] shows the fraction of increased positions for winning [losing] traders. Notably, losing traders show a higher fraction of increased positions than do winning traders across all trade groups.

- Place Figure 11 about here -

Next, Figure 11 presents the profitability of increased and non-increased positions. Consistent with our previous observations, the average ROI across all trades is significantly negative.[8] We observe that for all trades, non-increased positions have a smaller ROI than increased positions. However, single and copy trades differ from this observation. These trade groups exhibit a significantly smaller ROI for increased than for non-increased positions. Panels (b) and (c) of Figure 11 are restricted to trades with a positive and negative ROI, respectively. These panels provide an explanation for the observed group differences. The difference in profitability between non-increased and increased single

[8]Note that the reported ROI differs from the previously reported values, as our analysis in this section is restricted to trades that were opened and closed on different trading days.

trades is significantly more pronounced than for any other trade group. Panels (d) and (e) of Figure 11 present the ROIs for winning and losing traders, respectively. The leading trade group is noteworthy: The difference between increased and non-increased positions is significantly more pronounced for losing traders.

Building on the descriptive analysis, we model the probability of increasing existing positions using probit models. Our dependent variable is a dummy variable that takes value one if an existing position is increased (i.e., the same security is bought again), zero otherwise. Variable specifications are the same as in Section 2.3. Additionally, we introduce *Losing trade* variables for each trade group, similar to the $Profitable\ trade$ variables in Section 2.3. The marginal effects of our estimations are presented in Table 2. Across all groups, the probability of increasing an existing position is higher for losing trades. While single trades are approximately 12.5% more likely to be increased if the position is losing, this value is significantly smaller for social trades (approximately 9% for mirror trades and 10% for copy trades). Leader trades show the lowest marginal effect at approximately 8%. The number of followers ($Followers$) does not seem to have any influence on the probability of increasing an existing position (Model 2).

- Place Table 2 about here -

In Models 3-5, we replace our dummy variables denoting losing trades with a continuous variable capturing the current paper gains of an existing position. Models 3 and 4 highlight the group differences observed in Figure 11. While the propensity to increase an existing position decreases with the paper profits of a trade for single and copy trades, the opposite is true for leader and mirror trades. Leader trades are particularly more likely to be increased in the presence of paper profits. The group differences between single and leader trades are displayed in Figure 12. Panel (a) shows the decreasing probability (with confidence intervals) for single trades, and Panel (b) highlights the increasing probability with increasing paper profits. While losing positions have an approximately 21.5% chance of being increased, this probability decreases for winning trades to approximately 18%. Leader traders, by contrast, are more likely to increase a position when the existing position is winning. The observed differences between Models 1-2 and Models 3-4 for leader and mirror trades are consistent with the large differences in ROI between increased and non-increased positions displayed in Figure 11. Thus, although in general, the fraction of increased losing trades is larger than the fraction of increased winning trades, this effect is driven primarily by many increased trades with a small loss, while positions with a large paper loss have a lower probability of being increased.

- Place Figure 12 about here -

The number of followers does not generally seem to have any influence on the probability of increasing an existing position. To distinguish between profitable and losing trades, we again focus on leader trades (Model 5) and split the *Follower* variable. We observe significant differences between winning and losing positions here. For winning positions, our coefficient is not significantly different from zero, while for losing positions, the probability that leaders will increase the position increases with the number of followers. We argue that, in these cases, leaders use the position increase as a signal to demonstrate their confidence in their initial investment decision. The higher likelihood of leading trades being increased when a position loses value can be attributed to the unwillingness of investors to acknowledge a loss, not only to themselves but also to their followers. Selling an unprofitable trade could mean accepting that their strategy was incorrect. This might signal to followers a possible lack of knowledge and expertise. Conversely, buying more of a given security signals trust in own trading abilities and reinforces the belief in favorable future market movements. Weber and Zuchel (2005) report that escalation of commitment does not seem to be driven by a need to justify or rationalize an initial decision. Our evidence from social trading, however, indicates that this need at least contributes to moving decisions in the direction of escalation of commitment. Especially for leader traders, this behavior may be followed to send a signal to the users copying their investment strategies.

Our results indicate that the distinction between the two behavioral biases in question is not straightforward. While traders without social interaction suffer more from escalation of commitment − which is consistent with previous findings in the literature (Odean, 1998; Weber and Zuchel, 2005) −, leader traders, on average, are more prone to the house-money effect. Social traders however, seem particularly prone to follow those leaders that exhibit weak evidence of the house-money effect. This conclusion immediately follows from the fact that the marginal effect on $Profit$ is significantly smaller for mirror trades than for leader trades. It seems that more-sophisticated traders are less prone to escalation of commitment and more susceptible to the house-money effect, while less sophisticated traders are more vulnerable to escalation of commitment.

2.5 Risk-taking after realized losses

Finally, we analyze the behavior of investors after realized gains or losses. Hitherto, our analysis focused on paper gains and losses at the individual trade level. However, as documented by Imas (2016), realized and paper losses affect investment behavior in a different way. The author reconciles seemingly contradictory findings from the previous literature by showing that individuals avoid risk following a realized loss, but take on greater risk if the loss is not realized, a paper loss. Imas (2016) coins this finding the realization effect. In line with his results, we expect that traders decrease their risk-taking following a realized loss.

In order to account for realized gains or losses, we have to distance ourselves from the individual trade level and turn to a user level. We aggregate our individual trade data at the user level on a weekly basis. Then, we determine the performance of all trades realized in the previous week. We drop all user-month observations with no or ambiguous previous experience[9] and create a dummy variable *Realized losses* that equals one if the user closed a position at a loss in the previous week and zero if the user closed a position with a gain. In total, our weekly aggregated dataset contains 287,209 user-week observations.

For each user-week, we determine the average *Leverage* across all positions opened in a given week and the *Average investment* as the average amount invested in a position in a given week. We make use of the changes of these two variables to account for the change in risk-taking behavior of investors. First, we compare the change in *Leverage* of users' positions after realized gains and losses. Panel (a) of Figure 13 presents the results of our analysis separated by groups and for all groups together. Across all groups we observe a significant increase in risk-taking after realized losses. In contrast, after realized gains, single traders and social traders show evidence of decreased risk-taking. Leader traders still exhibit increased risk-taking after realized gains, but to a significantly smaller extend than following realized losses. The difference in the change in risk-taking between the different priors, realized gains and realized losses, are statistically significant as indicated by simple t-tests. Interestingly, the increase in risk-taking is significantly more pronounced for leader and social traders. We argue that leader traders have addi-

[9] In other words, we drop all users that did not realize gains or losses or realized both, gains and losses, in the previous week.

tional incentives to increase their risk-taking after realized losses in order to straighten their overall performance out and retain their followers. This increased risk-taking is transfered to the group of social traders by means of the following function.

- Place Figure 13 about here -

Panel (b) of Figure 13 presents similar results using an alternative measure to capture risk-taking behavior. In Panel (b), we use the *Average investment* per trade in a week to proxy for user risk-taking. Our argument is that putting more money, on average, in a single trade is associated with higher risk. Similar to Panel (a), we find that users show evidence for increased risk-taking after realized losses and decreased risk-taking after realized gains. All differences between the two priors are statistically significant as indicated by t-tests.

Finally, we focus on *Leverage* to proxy for the risk-taking of traders on the platform and estimate panel regressions with time-fixed and user-fixed effects to control for unobserved factors and analyze the influence of realized losses on risk-taking. More formally, we estimate regressions of the following form:

$$\Delta \text{Leverage}_{i,t} = \beta_1 \cdot \text{Realized losses}_{i,t} + \sum_{j=2}^{J} \beta_j \cdot \text{Controls}^j_{i,t} + u_i + v_t + \epsilon_{i,t}$$

Standard errors are clustered at the user level. As additional control variables, we determine and include the number of non-social trades, the number of social trades, the number of instruments the user uses to open positions, the average holding period, the number of followers for trades opened in the week, the number of users copied or mirrored on trades that week, and a variable to proxy for the degree of diversification that the investors employs. Lastly, we calculate different ratios capturing the fraction of leader trades and the fraction of mirror trades in a given week. The results of our panel regressions are presented in Table 3. Model 1 includes data on all trader groups. *Realized losses* enters the model with a significantly positive coefficient, underlining findings that users increase their risk-taking after previous realized losses. The remaining columns of Table 3 include group specific data. Model 2 only includes single traders. The results are similar to the overall findings. Models 3 and 4 contain data on leader and social traders, respectively. In line with Figure 13, the coefficient on *Realized losses* is significantly larger for these trader groups when compared to non-social traders.

- Place Table 3 about here -

Our findings are in contrast to the experimental results presented by Imas (2016) and cannot confirm the realization effect using individual trade data. In contrast, we find convincing evidence that investors increase their risk-taking both, after realized losses and after paper losses. Investors (in our dataset) do not seem to distinguish between paper losses and realized losses. Moreover, our results suggest that the increase in risk-taking is significantly larger for those users whose trading behavior is imitated by other users.

3 Conclusion

Our findings provide additional evidence for the disposition effect and could be explained by the reflection effect based on Kahneman and Tversky's prospect theory. The reflection effect indicates that investors are risk seeking in the loss domain but risk averse in the gain domain. Investors who face paper losses are risk seeking with respect to this security. They not only wait to sell the security (in the hope that the market moves in their favor, thereby allowing them to recover their loss while risking further losses) but also take the risk of investing in additional shares of the same security. If the market moves in their favor, investors exhibit risk-averse behavior and close profitable positions sooner, even if doing so entails only a small profit. Additionally, they have less incentive to buy an additional risky security. An alternative explanation for this behavior is the gambler's fallacy (see, e.g., Shefrin, 2008). We also present evidence for this kind of behavior following realized gains or losses. After a realized gains, users show evidence of decreased risk-taking while their risk-taking increases after realized losses.

We investigate the trading behavior of investors on a large social trading platform. The dataset allows us to differentiate among isolated traders, leaders (*investment advisers*), and *advice seekers* (mirror and copy traders). Our findings suggest a significant correlation between the number of users copying trading strategies and the manifestation of behavioral biases. Trades with many followers are less likely to be closed and more likely to be increased. This is especially pronounced for trades with negative paper gains. The monetary incentive and social recognition from being highly ranked could induce investors in leading trades to close them promptly to ensure an immediate improvement in their realized performance, which is visible to other users. Furthermore, revealing good performance could attract potential followers. Moreover, holding onto negative trades signals confidence to their followers about their financial strategy and does not adversely affect their realized performance or ranking because unrealized losses are not reflected in their end returns. Moreover, our results suggest that advice seekers are more likely to copy the investment strategies of advisors that exhibit a higher propensity to close winning positions early and refrain from increasing winning positions. In other words, advice seekers seem to be attracted by advisors susceptible to the disposition effect.

Our results have implications for investors on financial markets and open avenues for future research. First, investors may be able to uncouple from their biases when they understand that they are susceptible to them. Second, for investment advisors, our study highlights the importance of understanding the behavioral biases of their customers. Future research in this area should also focus on the question of whether investment advisors are less prone to certain biases and more susceptible to others or whether investment advisors exploit some of the behavioral biases to attract customers. In the context of social trading, it would be interesting to study whether leader traders might change their behavior to attract or retain followers.

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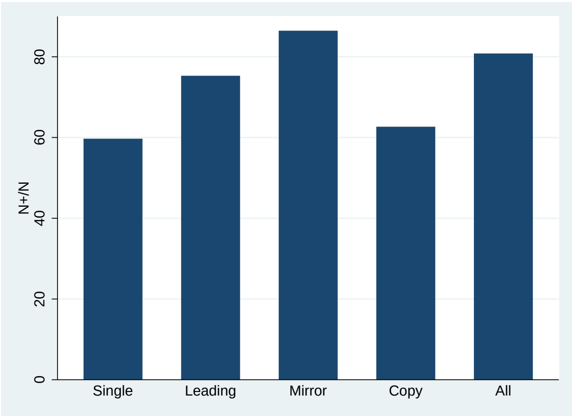
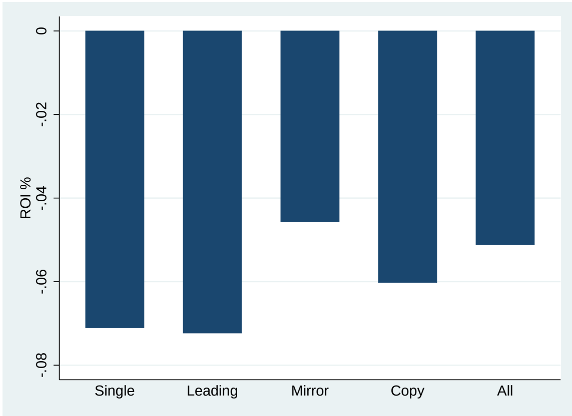
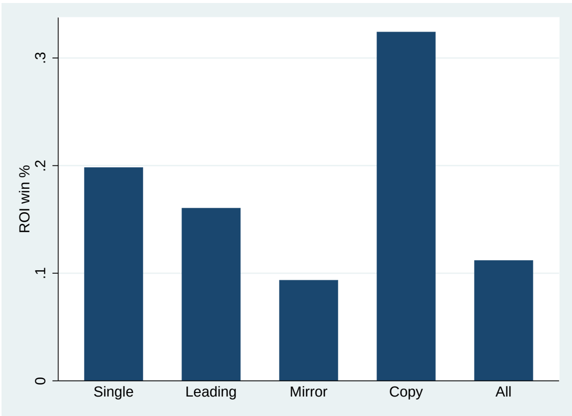


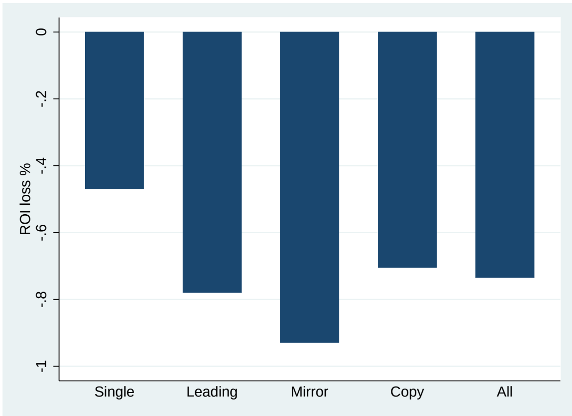
(a) Fraction of winning trades



(b) Mean ROI



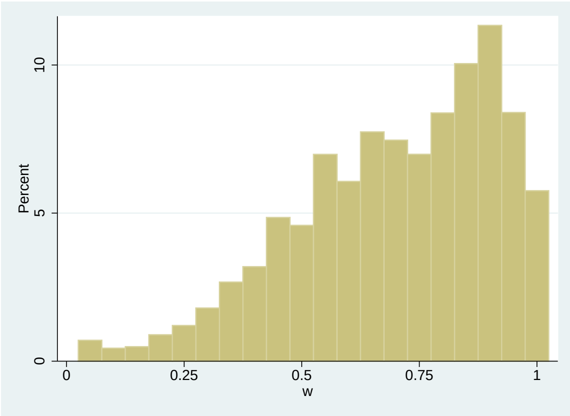
(c) Mean ROI of profitable trades



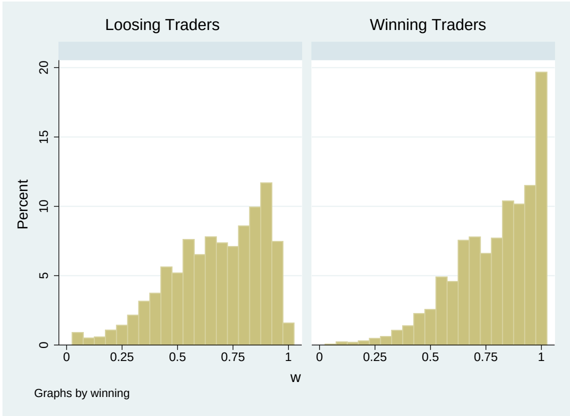
(d) Mean ROI non-profitable trades

Figure 1: Performance comparison of social and non-social trade types

The figure presents a comparison of the performance of different investors on a social trading platform. Panel (a) displays the fraction of profitable trades; Panel (b) displays the average return on investment by trade type. The bottom figures show the average return on investment for different trade types for profitable (Panel (c)) and non-profitable trades (Panel (d)). Data on trading behavior are from eToro. In total, our sample runs from January 1, 2012, to December 31, 2012, and contains 26.5 million trades from 79,922 investors.



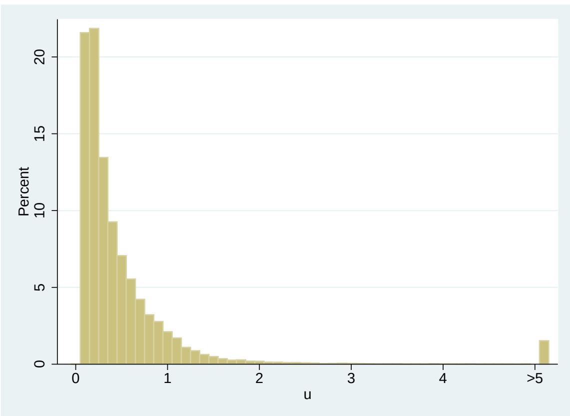
(a) Winning percentage: all traders



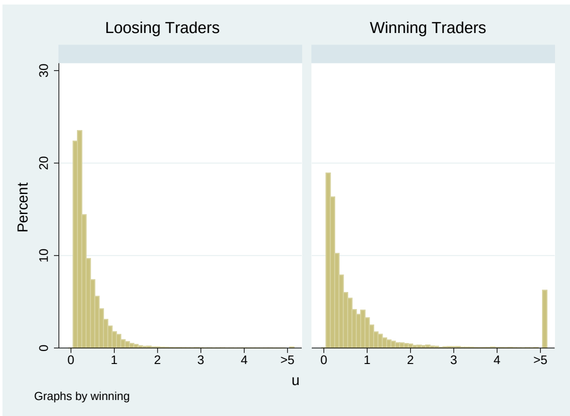
(b) Winning percentage winning vs. losing traders

Figure 2: Winning percentage: winning and losing traders

The figure shows the winning percentage of all traders (Panel (a)) and the winning percentage of losing and winning traders separately (Panel (b)). The winning percentage is calculated as $w = N_+/(N_+ + N_-)$, which measures the share of positive trades, N_+, to total trades, $N_+ + N_-$, of each trader. Data on trading behavior are from etToro. In total, our sample runs from January 1, 2012, to December 31, 2012, and contains 26.5 million trades from 79,922 investors.



(a) Win-loss ROI: all traders



(b) Win-loss ROI: winning vs. losing traders

Figure 3: Win-loss ROI ratio distribution

The figure shows the win-loss ROI ratio distribution given by $u = ROI_+/ROI_-$, which is the ratio between positive and negative ROIs. ROI_+ and ROI_- are the average ROIs of positive and negative trades for each trader. Panel (a) shows the distribution for all traders, and Panel (b) shows the distribution for losing and winning traders separately. Data on trading behavior are from eToro. In total, our sample runs from January 1, 2012, to December 31, 2012, and contains 26.5 million trades from 79,922 investors.

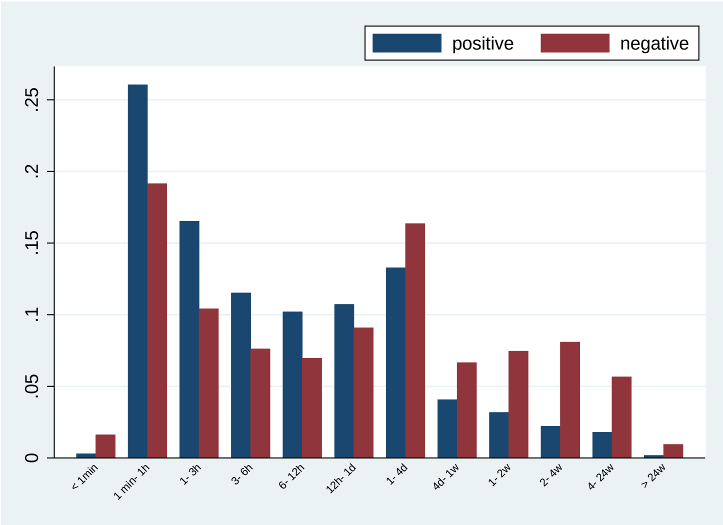
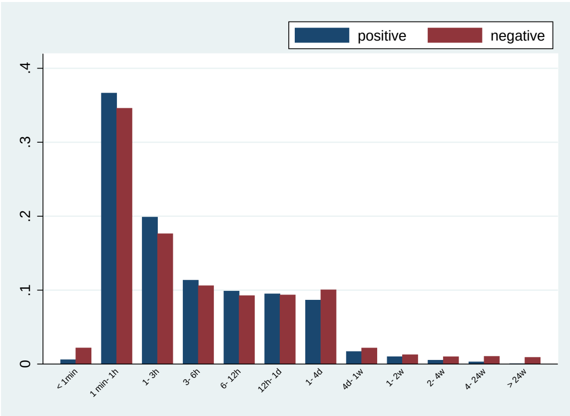
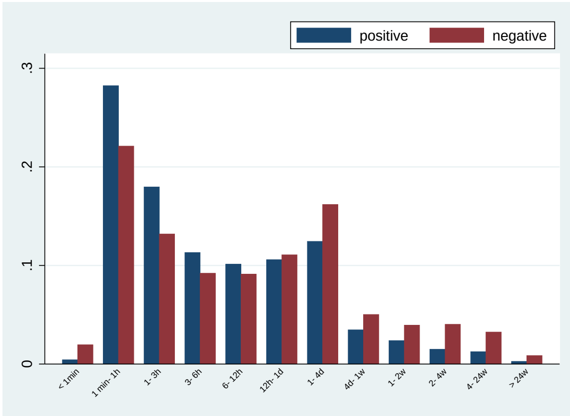


Figure 4: Holding time distribution of all trades

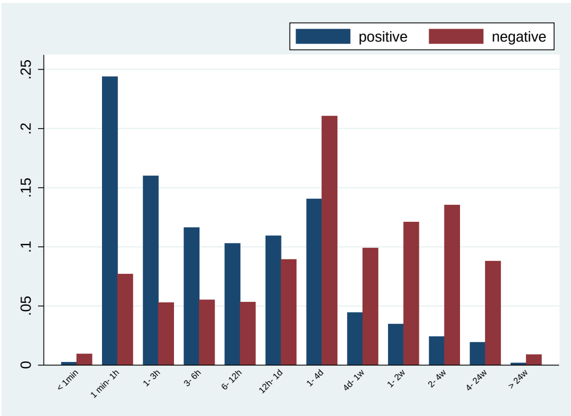
The figure shows the holding time, t, defined as the difference between a position's closing and opening time in milliseconds ($t = t_{closed} - t_{opened}$) for all traders. Data on trading behavior are from eToro. In total, our sample runs from January 1, 2012, to December 31, 2012, and contains 26.5 million trades from 79,922 investors.



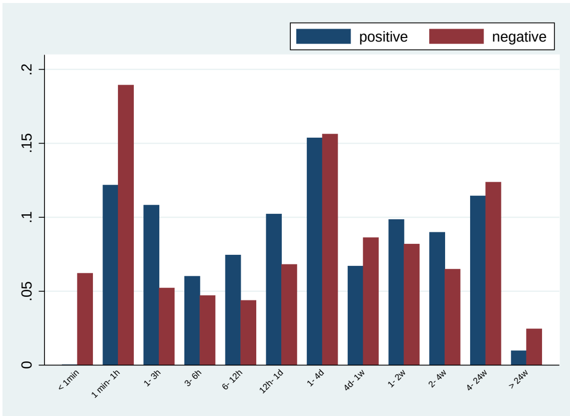
(a) Single Trades



(b) Leader Trades



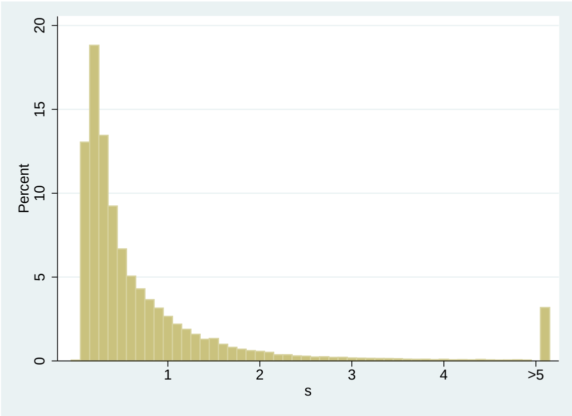
(c) Mirror Trades



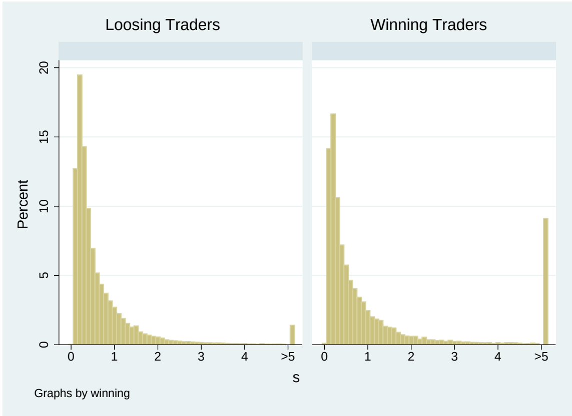
(d) Copy Trades

Figure 5: Holding time distribution of different trade types

The figure shows the holding time, t, defined as the difference between a position's closing and opening time in milliseconds ($t = t_{closed} - t_{opened}$) by trade groups. The top-left panel (a) shows the distribution for single trades, the top-right panel (b) shows leader trades, the bottom-left panel (c) shows mirror trades, and the bottom-right panel (d) shows copy trades. Data on trading behavior are from eToro. In total, our sample runs from January 1, 2012, to December 31, 2012, and contains 26.5 million trades from 79,922 investors.



(a) Win-loss holding time: all traders



(b) Win-loss holding time: winning vs. losing traders

Figure 6: Win-loss holding time distribution

The figure shows the win-loss holding time ratio, $s = t_+ / t_-$, which is defined as the ratio of the average holding times for positive, t_+, and negative trades, t_-, for each trader. Panel (a) shows the distribution for all traders, and Panel (b) shows the distribution for losing and winning traders separately. Data on trading behavior are from eToro. In total, our sample runs from January 1, 2012, to December 31, 2012, and contains 26.5 million trades from 79,922 investors.

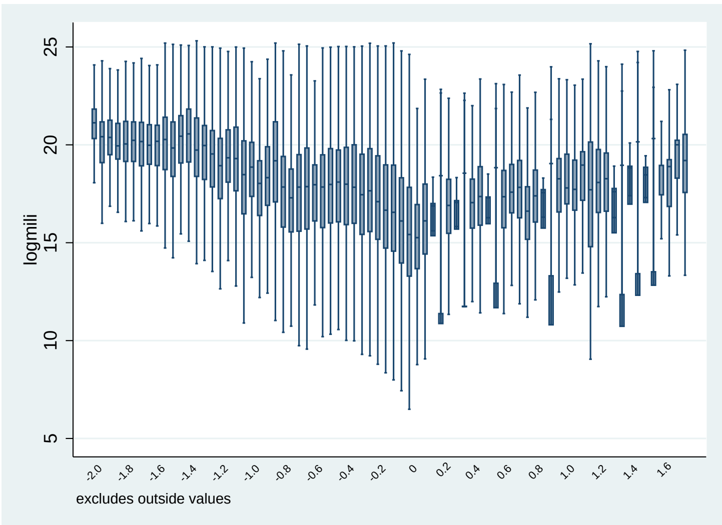
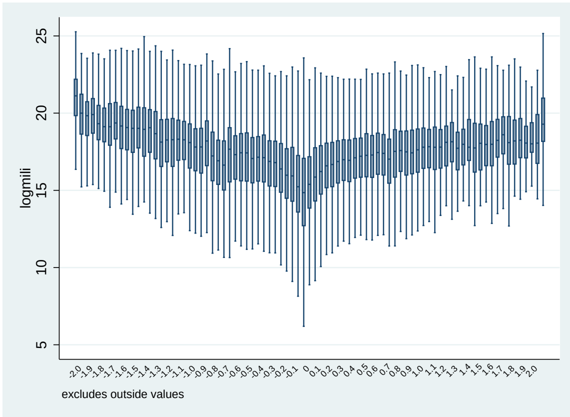


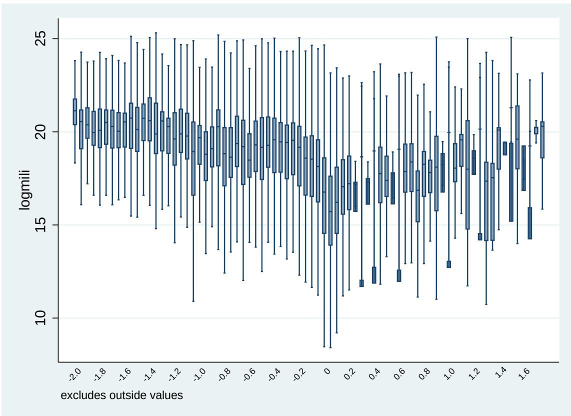
Figure 7: Holding time durations as a function of ROI

The figure shows box-and-whisker plots for the holding time durations as a function of ROI. Duration times are binned logarithmically ($\log(t)$) depending on the corresponding ROIs for all trades. Data on trading behavior are from eToro. In total, our sample runs from January 1, 2012, to December 31, 2012, and contains 26.5 million trades from 79,922 investors.

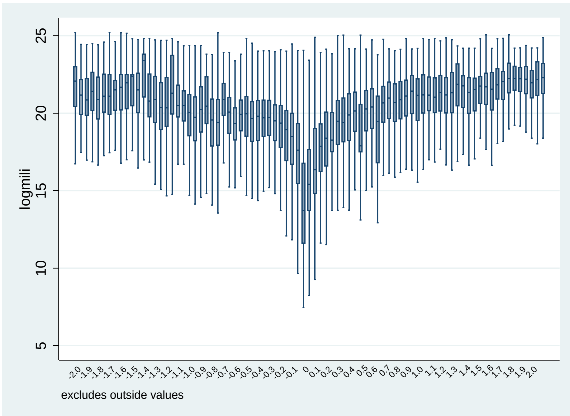
(a) Single Trades



(b) Leading Trades



(c) Mirror Trades



(d) Copy Trades

Figure 8: Holding time durations as a function of ROI for different trade types

The figure shows box-and-whisker plots for the holding time durations as a function of ROI. Duration times are binned logarithmically (log (t)) depending on the corresponding ROIs by trade groups. Panel (a) shows the distribution for single trades, Panel (b) shows leader trades, Panel (c) shows mirror trades, and Panel (d) shows copy trades. Data on trading behavior are from eToro. In total, our sample runs from January 1, 2012, to December 31, 2012, and contains 26.5 million trades from 79,922 investors.

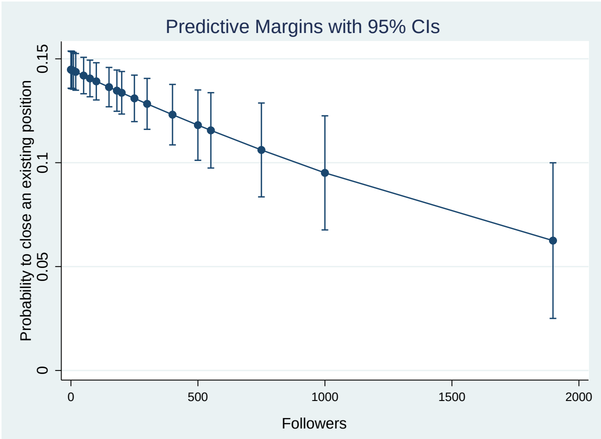
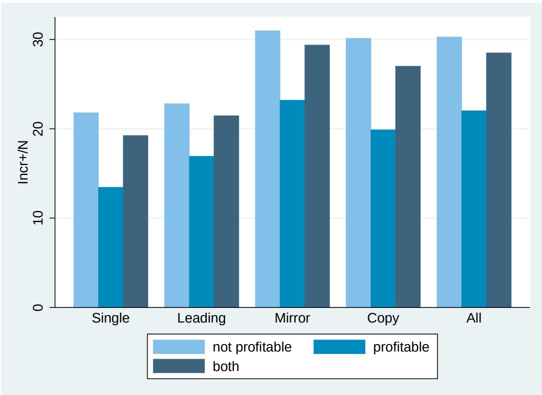
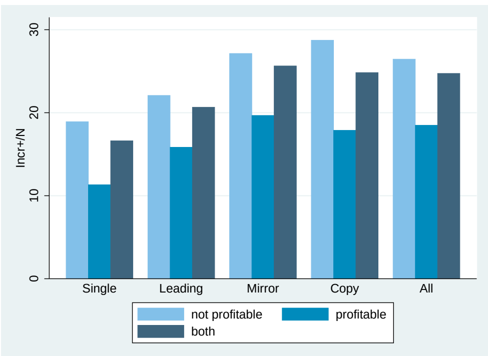


Figure 9: Probability of closing existing positions in *Followers*

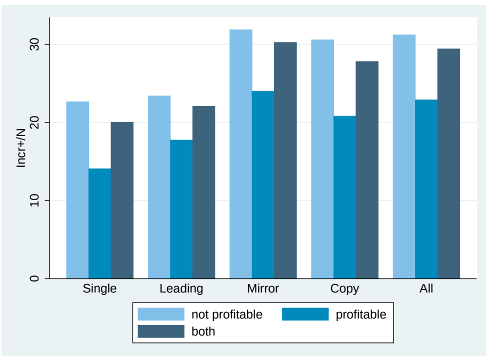
The figure shows the marginal effects from Model 4 presented in Table 1 evaluated at different values of *Followers*. Data on trading behavior are from eToro. In total, our sample runs from January 1, 2012, to December 31, 2012, and contains 26.5 million trades from 79,922 investors.



(a) All traders



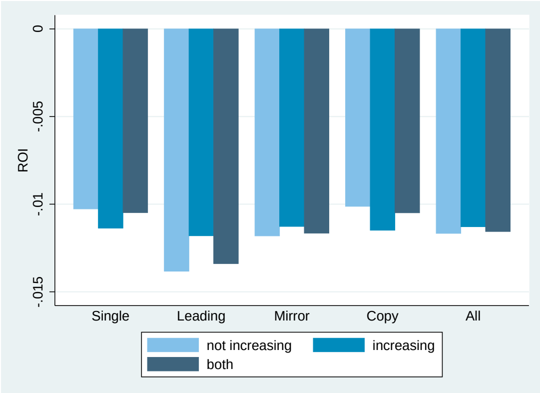
(b) Winning traders



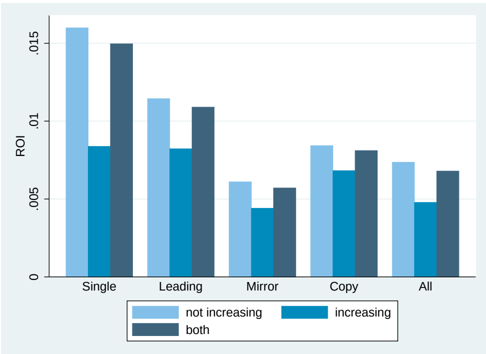
(c) Losing traders

Figure 10: Fraction of increased positions

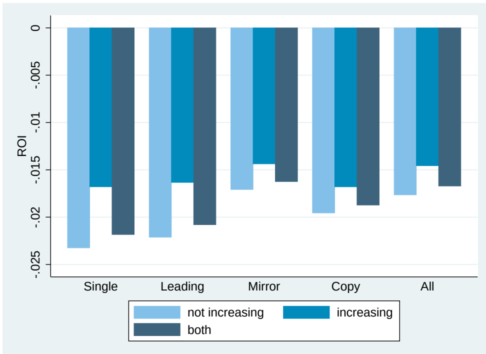
The figure shows the fraction of increased positions by trade groups. Panel (a) shows all traders, while Panel (b) [(c)] is restricted to winning [losing] traders. Each panel is divided into profitable and non-profitable trades. Data on trading behavior are from eToro. In total, our sample runs from January 1, 2012, to December 31, 2012, and contains 26.5 million trades from 79,922 investors.



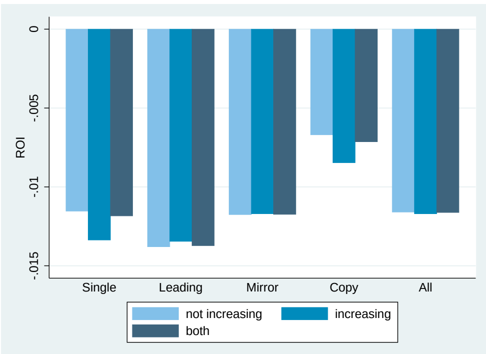
(a) All trades and traders



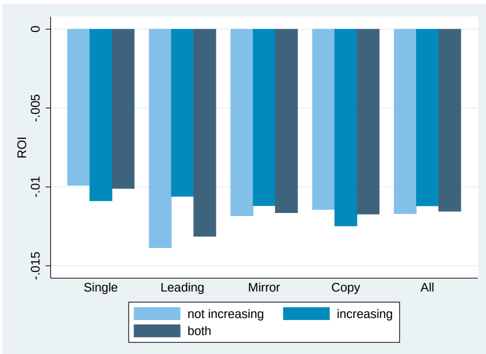
(b) Profitable trades



(c) Losing trades



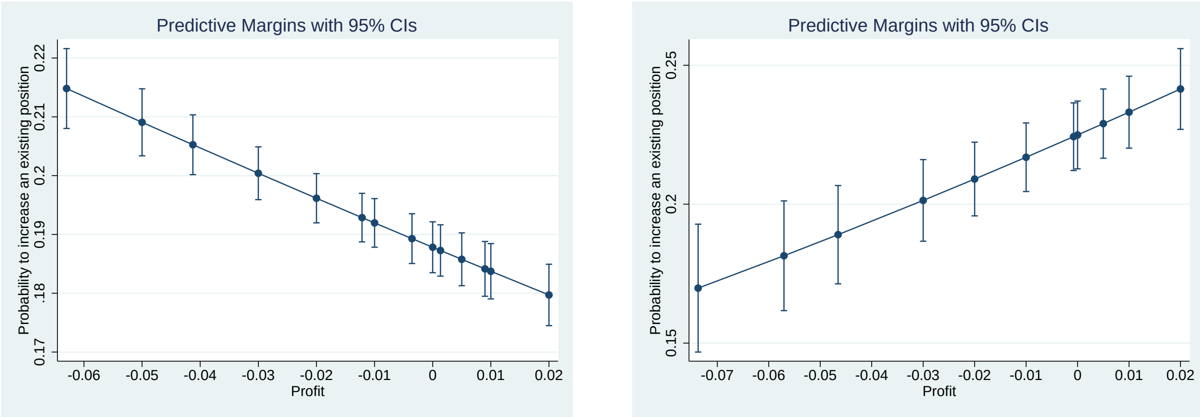
(d) Winning traders



(e) Losing traders

Figure 11: Profitability of increased and non-increased positions

The figure shows the profitability of increased and non-increased positions by trade groups. Panel (a) shows the ROI of all trades and traders. Panel (b) [(c)] is restricted to positions with a positive [negative] paper profit, while Panel (d) [(e)] shows the ROI separately for winning [losing] traders. Data on trading behavior are from eToro. In total, our sample runs from January 1, 2012, to December 31, 2012, and contains 26.5 million trades from 79,922 investors.

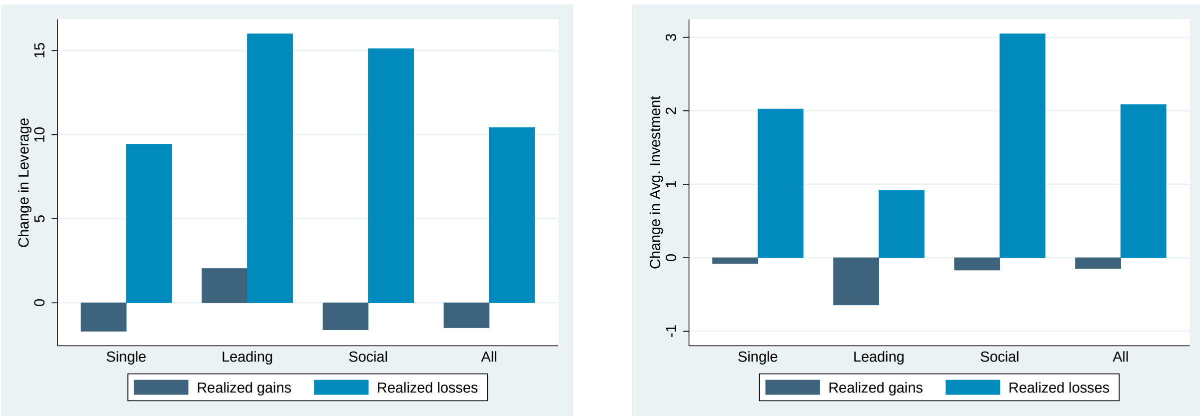


(a) Single trades

(b) Leader trades

Figure 12: Probability of increasing an unprofitable position for the leading trade type

The figure shows the marginal effects from variants of Model 4 presented in Table 2 evaluated at different values of $Profit$. Panel (a) shows marginal effects for single trades, while Panel (b) shows marginal effects for leader trades. Data on trading behavior are from eToro. In total, our sample runs from January 1, 2012, to December 31, 2012, and contains 26.5 million trades from 79,922 investors.



(a) Change in *Leverage*

(b) Change in *Average investment*

Figure 13: Risk-taking behavior after realized gains or losses

The figure shows the change in *Leverage* and *Average investment* of investors after realized gains or losses. *Leverage* denotes the average leverage of positions opened by investors in a week and *Average investment* denotes the average percentage of total assets invested in a position opened in a week. Data on trading behavior are from eToro. In total, our sample runs from January 1, 2012, to December 31, 2012, and contains 26.5 million trades from 79,922 investors. Weekly aggregated, our dataset contains 287,209 user-week observations.

	(1)		(2)		(3)		(4)		(5)	
Profitable trade, single trades	0.145	***	0.144	***						
	(0.002)		(0.002)							
Profitable trade, leader trades	0.204	***	0.205	***						
	(0.005)		(0.005)							
Profitable trade, mirror trades	0.254	***	0.254	***						
	(0.001)		(0.001)							
Profitable trade, copy trades	0.149	***	0.150	***						
	(0.002)		(0.002)							
Profit, single trades					6.829	***	6.813	***		
					(0.089)		(0.089)			
Profit, leader trades					8.253	***	8.346	***	4.728	***
					(0.261)		(0.260)		(0.177)	
Profit, mirror trades					11.035	***	11.088	***		
					(0.039)		(0.039)			
Profit, copy trades					5.513	***	5.484	***		
					(0.079)		(0.078)			
Followers			0.000	***			0.000	***		
			(0.000)				(0.000)			
Followers * Profitable trade									0.000	**
									(0.000)	
Followers * Losing trade									-0.127	***
									(0.005)	
Long			-0.034	***			-0.031	***	-0.047	***
			(0.001)				(0.000)		(0.005)	
Leader trades	-0.095	***	-0.095	***	-0.068	***	-0.067	***		
	(0.004)		(0.004)		(0.005)		(0.004)			
Mirror trades	-0.117	***	-0.12	***	-0.065	***	-0.066	***		
	(0.002)		(0.002)		(0.002)		(0.002)			
Copy trades	-0.132	***	-0.131	***	-0.141	***	-0.139	***		
	(0.002)		(0.002)		(0.002)		(0.002)			
Observations	80,696,684		80,696,684		80,696,684		80,696,684		1,094,476	
No. of Users	75,832		75,832		75,832		75,832		6,936	
Wald Chi^2	314,828	***	376,847	***	107,719	***	137,355	***	3,042	***
Pseudo R^2	0.21		0.21		0.18		0.18		0.18	

Table 1: Probability that investors will close an existing position

The table reports the marginal effects of our probit regressions. The dependent variable is a dummy variable taking value one if the open position is closed on that day. Standard errors are clustered at the individual investor level to mitigate possible issues due to heteroskedasticity and serial correlation. Standard errors are in parentheses. An asterisk denotes a p-value smaller than .05 (* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$). Data on trading behavior are from eToro. In total, our sample runs from January 1, 2012, to December 31, 2012, and contains 26.5 million trades from 79,922 investors.

	(1)		(2)		(3)		(4)		(5)	
Losing trade, single trades	0.125	***	0.127	***						
	(0.003)		(0.003)							
Losing trade, leader trades	0.084	***	0.078	***						
	(0.008)		(0.008)							
Losing trade, mirror trades	0.091	***	0.090	***						
	(0.001)		(0.001)							
Losing trade, copy trades	0.108	***	0.101	***						
	(0.003)		(0.003)							
Profit, single trades					-0.881	***	-1.257	***		
					(0.072)		(0.073)			
Profit, leader trades					0.681	***	0.72	***	2.142	***
					(0.219)		(0.211)		(0.227)	
Profit, mirror trades					0.174	***	0.097	***		
					(0.038)		(0.036)			
Profit, copy trades					-0.613	***	-0.767	***		
					(0.110)		(0.105)			
Followers			0.000				0.000			
			(0.000)				(0.000)			
Followers * Profitable trade									0.000	
									(0.000)	
Followers * Losing trade									0.112	***
									(0.007)	
Long			-0.086	***			-0.087	***	-0.065	***
			(0.001)				(0.001)		(0.009)	
Leader trades	0.050	***	0.047	***	0.044	***	0.039	***		
	(0.009)		(0.009)		(0.007)		(0.007)			
Mirror trades	0.126	***	0.12	***	0.121	***	0.116	***		
	(0.003)		(0.003)		(0.003)		(0.003)			
Copy trades	0.117	***	0.127	***	0.106	***	0.112	***		
	(0.006)		(0.006)		(0.006)		(0.005)			
Observations	80,696,684		80,696,684		80,696,684		80,696,684		1,094,476	
No. of Users	75,832		75,832		75,832		75,832		6,936	
Wald Chi^2	27,008	***	32,811	***	8,006	***	17,000	***	427	***
Pseudo R^2	0.02		0.02		0.01		0.02		0.02	

Table 2: Probability that investors will increase an existing position

The table reports the marginal effects of our probit regressions. The dependent variable is a dummy variable taking value one if the open position is increased on that day. Standard errors are clustered at the individual investor level to mitigate possible issues due to heteroskedasticity and serial correlation. Standard errors are in parentheses. An asterisk denotes a p-value smaller than .05 (* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$). Data on trading behavior are from eToro. In total, our sample runs from January 1, 2012, to December 31, 2012, and contains 26.5 million trades from 79,922 investors.

	(1)		(2)		(3)		(4)	
Realized losses	7.38	***	7.306	***	9.806	***	9.711	***
	(0.381)		(0.551)		(1.447)		(0.533)	
Leader trades ratio	-2.381	***			11.173	***		
	(0.751)				(1.486)			
Mirror trades ratio	-26.344	***					-33.097	***
	(0.895)						(0.989)	
Number of non-social trades	0.153	***	0.219	***	0.111	***	0.139	***
	(0.012)		(0.015)		(0.019)		(0.016)	
Number of social trades	0.024	***			0.003		0.027	***
	(0.002)				(0.003)		(0.002)	
Number of instruments	-0.197	***	-0.251	***	-0.381	***	-0.299	***
	(0.035)		(0.074)		(0.101)		(0.032)	
Diversification	2.404	***	0.168		1.128		2.111	***
	(0.552)		(0.860)		(1.007)		(0.384)	
Average investment	-0.072	*	-0.049		-0.214	***	0.018	
	(0.043)		(0.035)		(0.065)		(0.015)	
Average holding period	-0.016	***	-0.012	***	-0.013	***	-0.021	***
	(0.000)		(0.001)		(0.001)		(0.001)	
Number of users followed	0.401	***			0.102		0.298	***
	(0.044)				(0.121)		(0.047)	
Number of followers	0.001				0.001			
	(0.001)				(0.001)			
User fixed effects	Yes		Yes		Yes		Yes	
Time fixed effects	Yes		Yes		Yes		Yes	
Observations	678,740		291,616		56,980		361,553	
No. of Users	56,452		45,070		10,789		31,574	
F-Test	201.8	***	44.40	***	13.98	***	228.5	***
R^2	0.047		0.017		0.033		0.105	

Table 3: Risk-taking behavior after realized gains or losses

The table reports the results of our fixed effects panel regressions. The dependent variable is the average leverage of a user across all trades opened in a week. Column 1 contains data on all trader groups. Column 2 (3 / 4) contains data on single traders (leader traders / social traders). Standard errors are clustered at the individual investor level to mitigate possible issues due to heteroskedasticity and serial correlation. Standard errors are in parentheses. An asterisk denotes a p-value smaller than .05 (* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$). Data on trading behavior are from eToro. In total, our sample runs from January 1, 2012, to December 31, 2012, and contains 26.5 million trades from 79,922 investors. Weekly aggregated, our dataset contains 287,209 user-week observations.