About the Fear of Reputational Loss: Social Trading and the Disposition Effect*

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Abstract This article studies the relationship between giving financial advice and the disposition effect in an online trading environment. Our empirical findings suggest that leader traders are more susceptible to the disposition effect than investors that are not being followed by any other traders. Using a difference-in-differences approach, we show that becoming a financial advisor for the first time increases the disposition effect. This finding holds for investors who engage in foreign exchange trading as well as for investors who trade stocks and stock market indices. The increased behavioral bias may be explained by leaders feeling responsible towards their followers, by fear of losing followers when admitting a bad investment decision, or by an attempt of newly appointed leaders to manage their self-image.

Keywords: Behavioral finance, disposition effect, social trading, online trading platforms, peer advice.

JEL Classification: D14; G11; G23; G24.

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1 Introduction

Social trading as a novel way to participate in financial markets allows investors to observe the trading behavior of their peers and to follow their investment strategies. As literature provides convincing evidence that investors tend to value the advice of non-expert friends before making financial choices (Van Rooij et al., 2011), this suggests that social trading may alter investors' behavior. Indeed, Heimer (2016) shows that in a social trading environment, the *disposition effect* - i.e., the tendency of investors to forgo loss realization in favor of gain realization - tends to be higher than in a common trading setting where no social interactions among traders take place.[1] In contrast, Lukas et al. (2017) argue that the increased transparency of investors trading open to the public reduces the disposition effect in social trading. This paper contributes to this apparent contradiction and studies whether traders that are being followed by other investors are more or less susceptible to the disposition effect. Traders who are being followed by their peers engage in social interaction and are most closely monitored by their peers, which makes their trading activity most transparent.

It is not long ago that participants 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 investors to buy and sell securities with very low barriers to entry. In addition, these platforms allow investors to interact with one another and view other investors' trading activities, e.g., investments in a given stock and the profits made. Furthermore, investors can study and replicate others' trading strategies without the help of a professional broker to assist 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 these platforms (Motif Investing), and the U.S. Securities and Exchange Commission and other supervisory authorities have taken notice of their business model.

A commonly used feature of many of these platforms is the ability to copy the strategies of other traders on the platform, which can take place manually, referred to as *advice trading*, or automatically, referred to as *delegation trading*. We refer to the latter trades as "social trades" due to the social interaction involved.[2]

[1] Under the disposition effect, investors tend to be reluctant to close losing positions (Weber and Camerer, 1998; Odean, 1998). It refers to the tendency of investors to sell winners too soon (risk aversion after gains) while holding losers too long (risk seeking after losses), which is consistent with Kahneman and Tversky's Prospect Theory. Prospect Theory (Kahneman and Tversky, 1979; Tversky and Kahneman, 1992) 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. 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. 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, thereby increasing their willingness to hold a losing position for longer, in hope of reducing the loss - often referred to as the *reflection effect*. Note that, 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 possible 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).

[2] Although traders exploiting these possibilities do not directly pay commissions to the traders they duplicate, manual *advice trading* can be described as a form of investment advisory and automatic *delegation* trading,

We use the copy feature of social trading to categorize investors according to the degree of social interaction. In particular, we differentiate among investors who (i) execute trades on their own without engaging in any social interaction ("autonomous traders"), (ii) manually duplicate the investment strategies of other traders ("advice traders"), (iii) automatically duplicate the investment strategy of one or more selected other investors ("delegation traders"), and (iv) have their investment strategies copied by other investors ("leader traders").[3] Then, we investigate whether investment behavior differs significantly across these trader types. We study whether leader traders significantly differ from other investors with regard to their propensity for the disposition effect. Are leader traders attractive to their peers because their trading decisions are more rational and less emotional?

This study suggests that leader traders are significantly more susceptible to the disposition effect. So, either traders more susceptible to the disposition effect are more likely to attain followers, or, traders that are being followed and actively engage in social interaction increase their disposition effect. In order to study the peer pressure effect and isolate the mechanism driving our results, we perform (1) a probit analysis to determine whether the likelihood to increase the number of followers increases in the disposition effect and (2) a difference-in-differences analysis to study behavioral changes in investment decisions when investors are being followed for the first time.

This study adds additional insight to the existing list of possible explanations for why investment advisors might be prone to the disposition effect. Furthermore, it is the first to evaluate the underlying rationale of what drives leader traders and how leader traders are affected by their followers in a social financial environment. Exploiting a dataset containing approx. 150 million trading observations from 354,817 unique traders for the period from January 2012 through October 2015, this article also answers the following three research questions:

1. Are peer advisors (leader traders) less or more susceptible to the disposition effect?
2. Are investors with a larger disposition effect more likely to obtain followers? Or, do leader traders experience an increase in their disposition effect?
3. Finally, are leader traders indeed more successful in their investment decisions?

Evidence from the behavioral finance literature suggests that investors often fall victim to many different psychological and emotional biases in their decision-making under risk (Barberis and Thaler, 2003). Moreover, previous findings show that social interactions tend to significantly impact the behavior of investors. Qin (2012), for example, provides evidence that individuals have a tendency to observe other traders before making their own investment decisions. 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. Ammann and Schaub (2016)

as the management of the portfolio is, in a sense, delegated (Doering et al., 2015). Note that investors whose strategies are copied receive a payment for sharing their trading strategies. The amount of money received varies with the number of investors copying their strategy, the platform, and the success of their strategies. 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.

[3] Note that the trades executed by leaders can themselves be advice or delegation trades. Since the focus on this paper is on the disposition effect and the impact on investment leaders, we classify all trades that are being followed as leader trades.

find evidence that traders' communication tends to have an impact on the investment decisions of investors copying other investors' 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.

In a new strand of literature, Doering et al. (2015) discuss institutional aspects of social trading platforms. The authors argue that these 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 approx. 2.8% of its position size. Chen et al. (2014) analyze the role of social media in financial markets, focusing on the extent to which published articles on SeekingAlpha 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. They find a low correlation between the information exchanged and aggregate stock performance. More recently, Pelster et al. (2016) find that crowd stock assessments, released on the social trading platform Sharewise, can effectively explain stock returns.

The paper is organized as follows. The next section describes the data and discusses summary statistics. Section 3 presents our main results by analyzing the performance and trading behavior of different traders. In Section 4, we discuss several extensions to our main research questions. The last section discusses results and concludes.

2 Data

2.1 The Trading Platform

The following analysis is based on individual investors' transaction data from the online social trading platform *eToro*. The platform allows its traders to trade contracts for difference (CFD) that cover currency pairs, stocks, commodities and indices by taking short and long positions. Investors can start their trading activity after paying a minimum deposit amount, which varies between \$50 and \$300 based on a trader'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 an investor's trading history, risk levels, returns, and performance. Note that, among other statistics, the fraction of winning trades of the investor is displayed very prominently within this information.

eToro allows its investors to trade passively, meaning that other investors' trades are automatically copied, so-called *delegation* or *mirror trading*. The delegation trading mechanism gives investors the option to select any number of traders to be copied. Followed traders are copied proportionally, meaning that if the followed

[4]Chen et al. (2014) introduce three possible reasons as to why informed investors could have incentives to share their insights with other investors. These include 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.

trader risks 1% of her equity on a specific trade, then *eToro* will use exactly 1% of the trader's allocated equity to mirror that trade. Investors can allocate up to 100% of their equity to mirror any trader. Additionally, a trader can manually copy trades by other investors executed on the platform with the click of a mouse.

Our dataset consists of all trades that took place on the *eToro* platform between January 1, 2012, and October 8, 2015. In total, approx. 150 million trades were executed during that period by 354,817 traders. Regarding the different trade types, approx. 19.1% are autonomous, 1.6% are leading, 74.1% are delegation, and 5.1% are advice trades. While the data are heavily skewed towards delegation trades, even the smallest group contains almost 2.4 million trades, allowing a rigorous statistical analysis and a comparison across trade groups. Traders engaged in trading activity through 312 instruments. Among the instruments traded most heavily are foreign exchange rates, representing approx. 85% of all transactions. In addition to foreign exchange, several stock market indices (approx. 7% of all transactions), and some single name stocks are traded (approx. 1% of all transactions). Furthermore, investors engage in commodities and digital currency trading.

2.2 Variables

Our analysis builds on individual trade data and on weekly aggregated trade data. To be specific, for each trader, we aggregate the individual trade data on a weekly basis by using averages. In this way, we calculate the average number of trades per week—separated by trade types, the average holding period, the average investment as a fraction of overall wealth, the average leverage used, count the number of instruments used in a given week, count the number of other investors a given user follows in a week, and count the number of followers that follow a given investor. Moreover, we create a dummy variable `diversification` that takes the value one if a trader does not invest more than 20% of her wealth in a single trade, zero otherwise. Finally, we calculate the average return-on-investment (ROI) per trader-week as well as the standard deviation of the ROI for each trader-week.

To quantify the extent an investor is subject to the disposition effect, we follow Odean (1998) and Strahilevitz et al. (2011). At the end of each trading day, we count the trades that are closed at a profit (loss) as *realized gain* (*realized loss*) and the trades that are not closed at a price that is higher (lower) than the purchase price as a *paper gain* (*paper loss*). Then, the size of the disposition effect is estimated as the difference between the proportion of realized gains and the proportion of realized losses:

$$\text{Disposition effect} = \frac{\#\text{ realized gains}}{\#\text{ realized gains} + \#\text{ paper gains}} - \frac{\#\text{ realized losses}}{\#\text{ realized losses} + \#\text{ paper losses}}. \quad (1)$$

An investor who sells all trades that are in-the-money at the end of the observation period and holds on to all trades that are out-of-the money, exhibits a maximum disposition effect of one. Vice versa, an investor who only keeps positions that are in-the-money, exhibits a minimum disposition effect of minus one. If the trader equally closes profitable and non-profitable positions, her disposition effect is zero.

Summary statistics of our trade data are presented in Table 1. The statistics indicate that, while on average, trades yield a negative return, the vast majority of trades yield positive returns.[5] Similarly, the holding period (in minutes) is skewed, with many short records. Moreover, we observe that investors, on average, use significant amounts of `Leverage`, which may be explained by the high fraction of trades taking place in foreign exchange. Summary statistics for weekly aggregated trade data are shown in Table 2.

	Obs	Mean	SD	P25	P50	P75
Winning trade	149,967,788	0.795	0.404	1	1	1
ROI	149,338,148	−0.0001	0.005	0.00005	0.0004	0.001
Holding period	149,373,774	6,762.341	36,411.290	55.583	302.367	1,920.850
Leverage	149,977,370	101.377	110.437	25	50	100
Investment	149,977,370	4.463	11.307	0.170	0.540	2.380
Long	149,977,370	0.546	0.498	0	1	1
Autonomous trade	149,977,370	0.191	0.393	0	0	0
Leader trade	149,977,370	0.016	0.125	0	0	0
Delegation trade	149,977,370	0.741	0.438	0	1	1
Advice trade	149,977,370	0.051	0.221	0	0	0
Number of followers (leader only)	2,378,983	41.683	261.724	1	2	6
Number of followers (all trades)	149,977,370	0.793	33.716	0	0	0

Table 1: Summary statistics of the trade data

The table shows summary statistics of the trade data. Data on trading behavior are from eToro. In total, our sample runs from January 1, 2012, to October 8, 2015, and contains approx. 150 million trades from 354,817 investors.

3 Empirical Strategy and Results

3.1 The Disposition Effect in Social Trading

We begin our analysis by presenting several descriptive statistics analyzing the performance and trading behavior of the different trader 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 trades than losing trades. Moreover, we find that the fraction of winning trades is highest for delegation trades (consistent with Pan et al., 2012; Liu et al., 2014) and lowest for autonomous trades. The fraction of winning trades for leader trades is lower than that for delegation 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 delegation trades. Hence, most followers seem to be able

[5] `Winning trade` is a dummy variable taking a value of one if a trade is closed with a profit, zero otherwise.

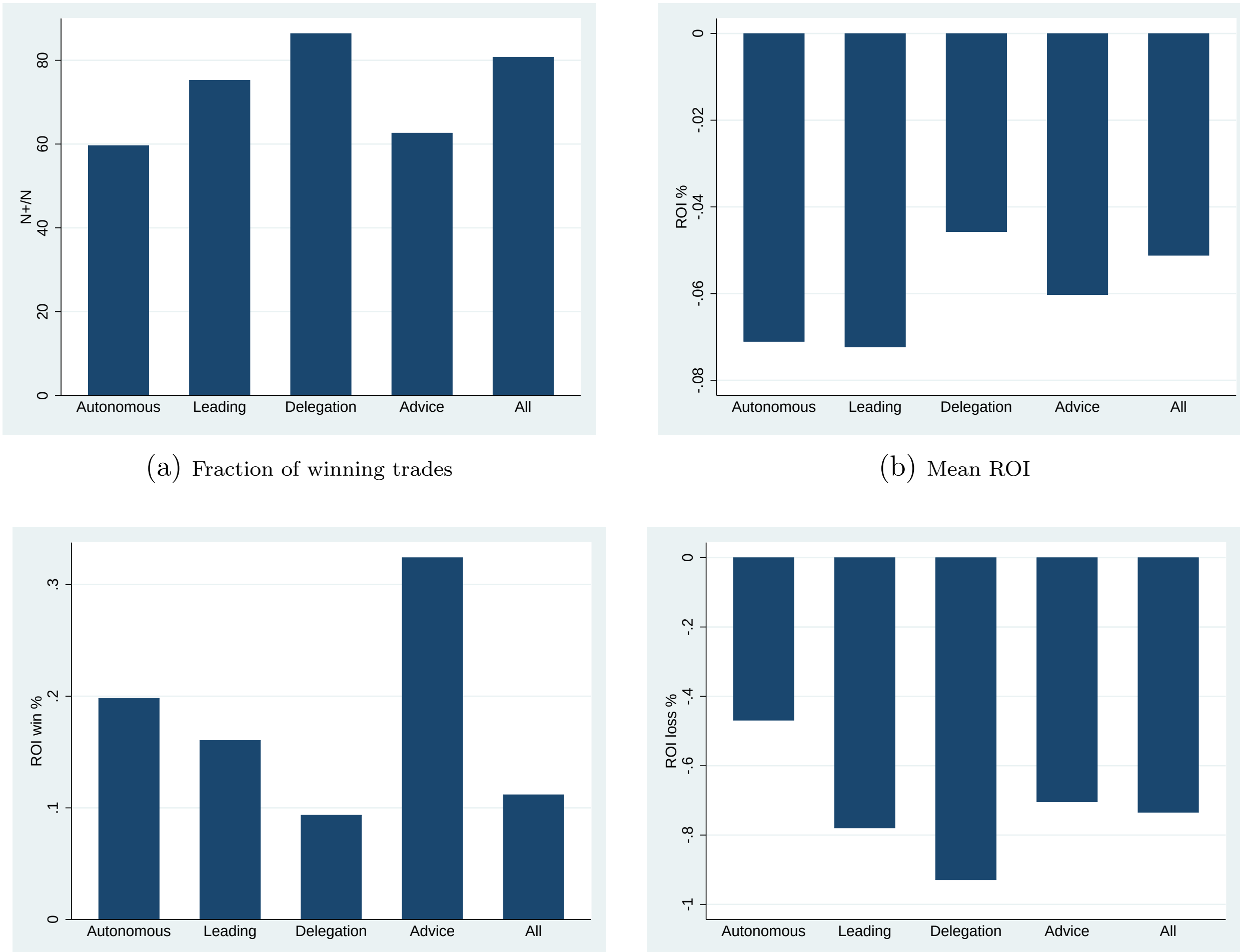
Variable	Obs	Mean	Std. Dev.	P25	P50	P75
Disposition effect	5,190,928	0.400	0.365	0.114	0.428	0.669
Avg. ROI	5,807,855	−0.001	0.008	−0.001	0.0002	0.001
SD ROI	5,019,284	0.005	0.013	0.001	0.003	0.006
No. individual trades	5,807,890	5.010	30.373	0	0	3
No. advice trades	5,807,890	1.150	8.078	0	0	0
No. delegation trades	5,807,890	18.722	53.015	0	4	17
Avg. holding period	5,807,890	206.044	643.155	14.907	49.426	146.660
Avg. investment	5,807,890	11.627	30.135	0.816	2.644	11.790
Diversification	5,807,890	0.750	0.433	0	1	1
Avg. leverage	5,807,890	92.828	91.866	35.000	66.237	100.000
No. instruments	5,807,890	4.145	3.886	1	3	6
No. followed traders	5,807,890	0.984	2.051	0	0	1
Number of followers	5,807,890	1.590	54.954	0	0	0

Table 2: Summary statistics of weekly aggregated trade data

The table shows summary statistics of the weekly aggregated trade data variables. Data on trading behavior are from eToro. In total, our sample runs from January 1, 2012, to October 8, 2015, and contains approx. 150 million trades from 354,817 investors.

to select the "right" investors to follow (i.e., followers seem to be able to specifically identify those investors that have a high ratio of winning trades).

When considering the return-on-investment or ROI, the situation is quite different (see Panel (b) of Figure 1). On average, and across all groups, ROI is negative. Differences between groups are minor, except for the delegation 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 that 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. Delegation trades, on average, generate significantly ($p < 0.01$) less profitable ROIs than the other three trade types, while profitable advice trades exhibit the highest ROI. Similar to non-profitable trades, delegation trades generate significantly lower ROIs, on average, than autonomous and leading trades. For losing trades, autonomous 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, autonomous trades significantly outperform ($p < 0.01$) social trades (delegation and advice trades), despite being less likely to realize a profitable trade. This is because the average ROI of profitable and unprofitable autonomous trades is significantly higher than those of social trade types. Although delegation trades are the most likely to realize a profitable trade, the average ROI is smaller than that for autonomous trade types. In summary, social trading does not significantly improve the performance of investors.



(a) Fraction of winning trades

(b) Mean ROI

(c) Mean ROI of profitable trades

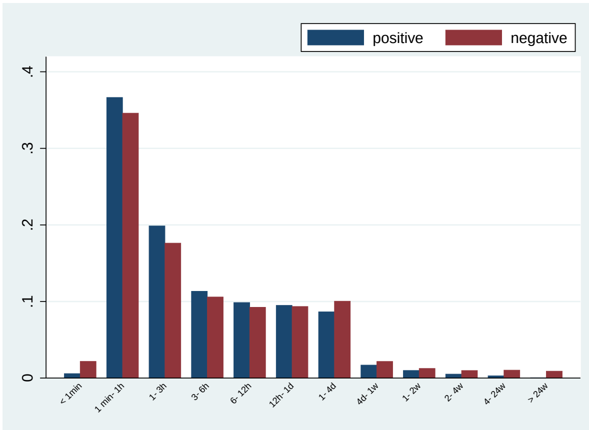
(d) Mean ROI of non-profitable trades

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

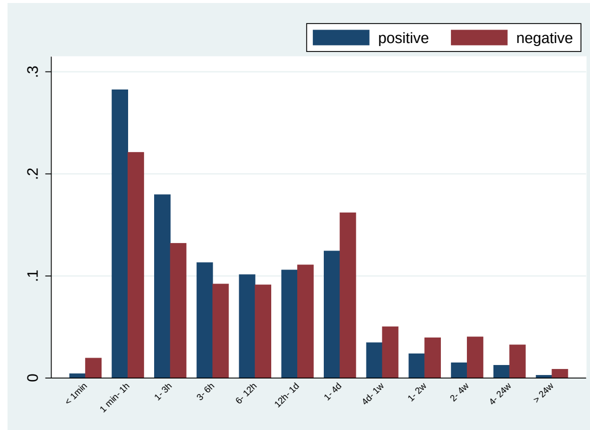
The figure presents a comparison of the performance of different investors on a social trading platform. Panel (a) displays the fraction of profitable trades; Panel (b) displays the average return on investment by trade type. The bottom figures show the average return on investment for different trade types for profitable (Panel (c)) and non-profitable trades (Panel (d)). Data on trading behavior are from eToro. This figure is based on a subsample of our data, covering the year 2012 which contains 26.5 million trades from 79,922 investors.

3.1.1 Security Holding Time

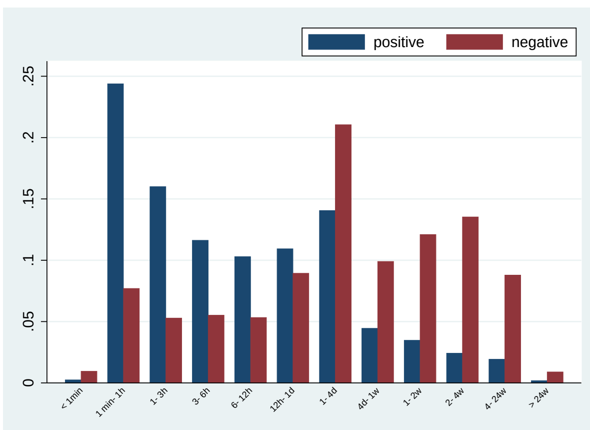
The disposition effect may depend on the average holding time of securities. The holding time, t, is defined as the difference between a position's closing and opening time in milliseconds ($t = t_{closed} - t_{opened}$). Holding time distributions for positive and negative trades are calculated separately, based on their ROI. Positions exactly breaking even are excluded. Across all groups, more than half of all positions are held no longer than one day. Only approx. 5% of all trades are held for longer than one month. This highlights that the network constitutes a trading rather than an investment platform. We present the holding time distributions of positive and negative trades for different trade types in Figure 2. 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 than negative trades (except for holding times of less than one minute).



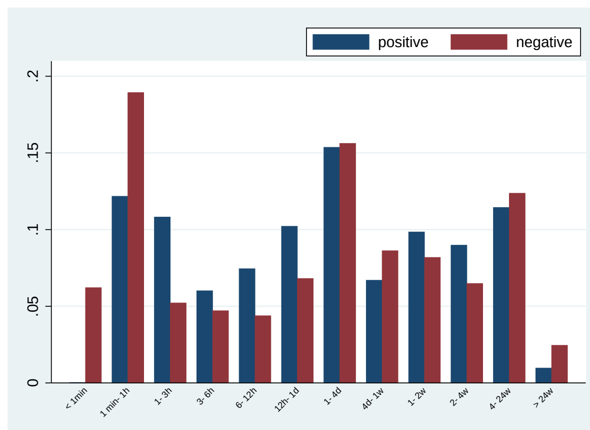
(a) Autonomous trades



(b) Leader trades



(c) Delegation trades



(d) Advice trades

Figure 2: 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 autonomous trades, the top-right panel (b) shows leader trades, the bottom-left panel (c) shows delegation trades, and the bottom-right panel (d) shows advice trades. Data on trading behavior are from eToro. This figure is based on a subsample of our data, covering the year 2012 which contains 26.5 million trades from 79,922 investors.

From autonomous through leader to delegation trades, the likelihood that positive trades have a significantly 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 delegation trades.

Although delegation 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 advice trades.[6] 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 delegation trades automatically copy leading trades, the variations between the distributions of delegation 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).

3.1.2 The Disposition Effect

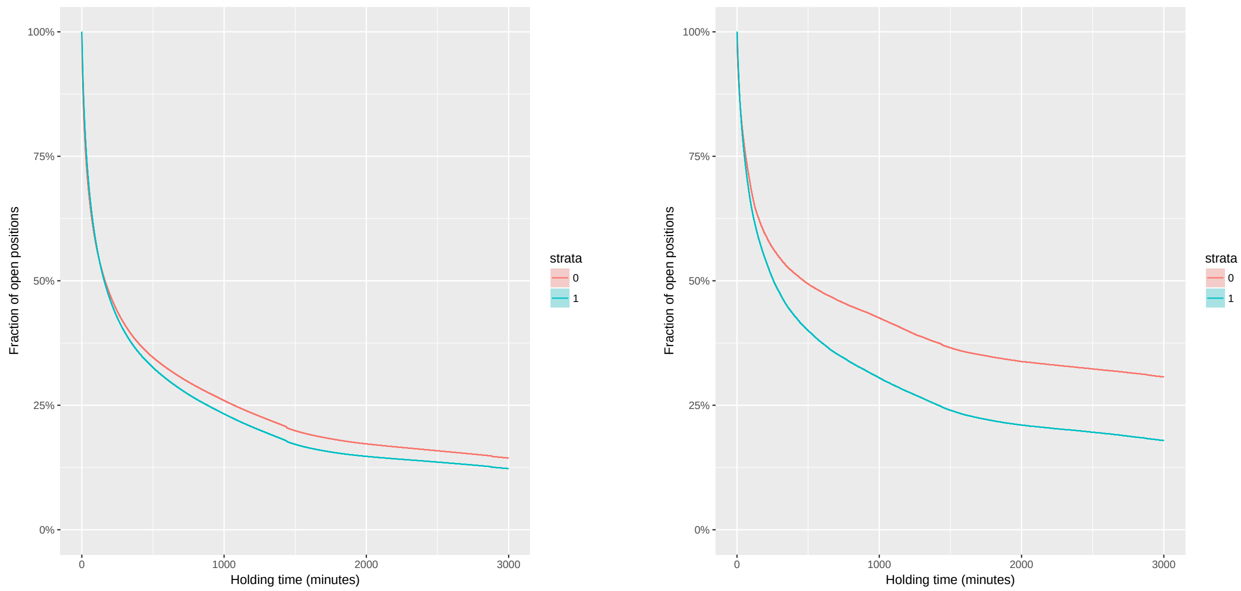
We visualize the disposition effect by plotting the estimates of Kaplan-Meier survival functions, separately for autonomous traders and for leader traders. The Kaplan-Meier survival functions represent the cumulative densities of open trades as a function of holding time and are based on an indicator variable that equals one if a position is closed, zero otherwise. For each plot, separate survival functions are shown, depending on whether the trades are closed at a gain or at a loss, respectively. The disposition effect reveals itself whenever there are more realized gains than losses for a given holding period, i.e. whenever the survival function of the realized losses exceeds that of the realized gains. The magnitude of the gap between the survival functions measures the size of the disposition effect. Figure 3 indicates that both autonomous and leader traders are subject to the disposition effect. Most interestingly, the disposition effect illustrated by Kaplan-Meier survival functions is more pronounced for leader traders. Thus, this first preliminary evidence suggests that leader traders differ substantially in their trading behavior as compared to autonomous traders.

3.2 Determinants of the Probability of Closing Existing Positions

What are the determinants of the probability of traders closing existing positions? As suggested by the descriptive data above, we predict (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 traders as well as for leader traders. Furthermore, we are interested in the role that followers may play when leader traders decide to close their positions. Leader traders' decisions may be influenced by a large audience (i.e., a large number of followers). For example, leader traders may be especially reluctant to close losing positions when they have a large audience, as the realization of negative profits signals a poor investment decision to the followers. Therefore, leaders may be even more likely to hold losing positions open for longer, still hoping for positive returns.

A probit model is used to predict the probability of closing positions, implying some interaction between covariates even when there would be no explicit product term in the model. In this way, every marginal effect depends on the values of all independent variables and includes a contribution from all other covariates in the model. This marginal effect of a variable on Pr(Y) declines as a change in a variable pushes Pr(Y)

[6]Some leader traders are delegated to or copied more often than others, which places greater weight on their decisions, or some delegation or advice trades may be closed manually by the trader holding the position. This would be the case when an investor decides to no longer follow the given leader.



Autonomous trades

Leader trades

Figure 3: Holding period of gains and losses for autonomous and leader traders

The figure shows the estimates of a Kaplan-Meier survival function. The estimates are based on an indicator variable that equals 1 if a position is closed, 0 otherwise. Both figures depict separate survival functions for winning (green, strata = 1) and losing (red, strata = 0) positions. The left panel (a) shows the distribution for autonomous trades, the right panel (b) shows leader trades. Data on trading behavior are from eToro. In total, our sample runs from January 1, 2012, to October 8, 2015, and contains approx. 150 million trades from 354,817 investors.

towards 0 or 1 (see, e.g., Berry et al. (2010, p. 251), who refer to this phenomenon as *compression*).[7] In this analysis, we include all positions that were opened and closed on different trading days. The dependent variable `Close` is a dummy variable taking value one on the day when a position is closed, zero otherwise. The independent variable of interest is `Profitable trade`. It is also a dummy variable that takes value one when the position exhibits positive paper profits, zero otherwise.

To determine whether a position is winning or losing, we compare the purchase price with the closing price on each given day. Formally, we estimate the following model:

$$\Pr(\texttt{Close})_{it} = \sum_i \texttt{Profitable trade}_{it} \times \texttt{Trade group}_i + \texttt{Followers}_{it} + \texttt{Controls}_{it} + \epsilon_{it},$$

where `Trade group` denotes a dummy variable that captures the group of trades to which a specific trade belongs. Using the interaction terms with the dummy variables, we split our explanatory variable in four distinct variables, one for each trade group. For example, the variable `Profitable trade, autonomous trades` takes value one if the position currently exhibits positive paper profits and is an autonomous trade, zero otherwise. We employ the separate variables to study differences across trade groups. As control vari-

[7] These built-in interactions from nonlinear responses are included in the prominent discussion by Ai and Norton (2003).

ables, we include a dummy for the trade group (autonomous trades are the baseline) and a dummy variable that captures whether the position is a long or short position (`Long`). We include month dummies to control for unobserved heterogeneity in overall trading behavior. Table 3 presents the models to analyze the investors' propensity to close winning positions sooner than losing positions. Standard errors are clustered at the investor level. As standard errors in the multivariate regression framework decrease in sample size, the dimensions of our sample will yield statistically significant results beyond conventional levels of significance. We cope with this issue by focusing on the economic significance of our results and thus present marginal effects. Additionally, we repeat our main analysis with smaller subsamples of equal group size in a bootstrapping exercise. The results of the additional analyses confirm our findings and are presented in Table 4.

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 autonomous trades, the probability that the position is closed on a given trading day increases by 14.4% if the position is currently profitable. This result is even more pronounced for leader trades (20.5%). For delegation trades, this effect is the most pronounced. Here, the probability of closing an existing position increases by 25.4% if the position is profitable.

In order to study whether leader traders are particularly reluctant to close losing positions when they have a large audience, it seems intuitive to restrict the sample to leader trades. Then, we introduce the number of followers (`Followers`) as an additional independent variable in Model 2. While the coefficient on `Followers` is negative, the economic effect is not significant. Overall, the size of the audience does not seem to meaningfully influence a leader's propensity to close an existing position. In Models 3-4, 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.

We can examine in greater detail the influence of having many followers on the probability of closing an existing position. We hypothesize that having a larger audience negatively influences this probability only for losing trades. We believe that leaders are more concerned about closing a losing position when they have a large number of followers. By maintaining a losing position, the leader does not admit having made an incorrect investment decision. Admitting one's fault is especially painful when a large group of investors follows one's trading strategy. Moreover, the paper loss will not affect his percentage of winning trades until it is realized. For the analysis, we split the variable `Followers` by `Profitable trade`. Model 5 provides evidence in support of our hypothesis. In the model, we study whether the influence of followers on the propensity to close a position differs between winning and losing trades. 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.

Note that investor characteristics represent one possible explanation for the observed group differences. Although the dataset does not allow us to directly control for investor characteristics, advice traders could be more experienced than delegation traders.[8] Advice trade types are the least prone to the disposition

[8] 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).

	(1)	(2)	(3)	(4)	(5)
Profitable trade, autonomous trades	0.144				
	(0.002)				
Profitable trade, leader trades	0.205	0.223			
	(0.005)	(0.006)			
Profitable trade, delegation trades	0.254				
	(0.001)				
Profitable trade, advice trades	0.150				
	(0.002)				
Profit, autonomous trades			6.814		
			(0.089)		
Profit, leader trades			8.348	8.598	4.728
			(0.259)	(0.292)	(0.177)
Profit, delegation trades			11.089		
			(0.039)		
Profit, advice trades			5.484		
			(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	-0.048	-0.031	-0.045	-0.047
	(0.001)	(0.005)	(0.000)	(0.005)	(0.005)
Leader trade	-0.098		-0.070		
	(0.004)		(0.005)		
Delegation trade	-0.120		-0.066		
	(0.002)		(0.002)		
Advice trade	-0.131		-0.139		
	(0.002)		(0.002)		
Observations	80,696,684	1,094,476	80,696,684	1,094,476	1,094,476
No. of Traders	75,832	6,936	75,832	6,936	6,936
Wald Chi^2	376,580	3,540	137,365	2,006	3,042
Pseudo R^2	0.21	0.15	0.18	0.16	0.18

Table 3: Probability that investors will close an existing position (marginal effects)

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. As standard errors in the multivariate regression framework decrease in sample size, the dimensions of our sample will yield statistically significant results beyond conventional levels of significance. In light of this observation, we focus on the economic significance and present marginal effects. Data on trading behavior are from eToro. This table is based on a subsample of our data, covering the year 2012 which contains 26.5 million trades from 79,922 investors. We repeat our main analysis with several smaller subsamples of equal group size in a bootstrapping exercise and present the results in Table 4.

effect. In contrast to the delegation trade type, advice 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.[9]

However, considering both delegation and advice 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, delegation traders in particular seem to be highly susceptible to such a 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.[10] Generating frequent profitable positions, i.e., closing profitable positions sooner to take a small profit or ROI, signals "good performance" (in terms of winning trades percentage) to (potential) followers. Closing negative positions not only deteriorates one's overall performance but can also deter (potential) followers. In summary, the empirical evidence in this study suggests that leader traders are more susceptible to the disposition effect than investors that are not being followed. Delegation traders seem to be particularly susceptible to this behavioral bias, that is, delegation traders are more likely to follow leaders that experience a very high disposition effect.

As robustness checks and to address possible implications of our dataset being (a) highly skewed toward mirror trades and (b) very large, we perform additional analyses. We simultaneously address both issues by repeatedly drawing smaller samples of equal group size from our dataset and repeating our analyses using the smaller datasets. We randomly draw 10,000 observations from each group and estimate Model 1 of Table 3. We repeat this exercise 5,000 times and present summary statistics of the resulting distribution in Table 4. The findings are in line with the ones discussed above, although they are marginally larger than in our main analysis. We observe a positive marginal effect for each trade group that is economically significant. Marginal effects vary across trade groups, with delegation trades exhibiting the highest probability, followed by leader trades. Autonomous and advice trades display similar marginal effects with an increase of 16%.

[9]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).

[10]It may be the case that the disposition effect is stronger for delegation trade types than for leading trade types because, on average, delegation trade types more often follow leading trade types with a higher disposition effect. Another possible explanation is that investors with many followers become more susceptible to the bias.

Variable	Obs	Mean	SD	Min.	Max.	P5	P95
Profitable trade, autonomous trades							
Marginal effect	5,000	.163	.006	.143	.181	.153	.172
t statistic	5,000	26.038	.937	22.767	29.175	24.505	27.578
Profitable trade, leader trades							
Marginal effect	5,000	.228	.007	.206	.25	.217	.239
t statistic	5,000	25.556	1.145	21.867	29.881	23.692	27.463
Profitable trade, delegation trades							
Marginal effect	5,000	.284	.007	.26	.31	.272	.296
t statistic	5,000	38.958	.971	35.441	42.338	37.336	40.566
Profitable trade, advice trades							
Marginal effect	5,000	.164	.008	.138	.198	.151	.177
t statistic	5,000	20.527	.949	16.955	23.99	18.96	22.095

Table 4: Summary statistics of bootstrapping exercise: Probability that investors will close an existing position (marginal effects)

The table shows summary statistics of the distributions of our main variables of interest that result from repeatedly ($N = 5,000$) drawing random samples from our dataset and estimating probit regressions as documented in Section 3.2. We randomly draw 10,000 observations from each group and estimate Model (1) from Table 3. Data on trading behavior are from eToro. In total, our sample runs from January 1, 2012, to October 8, 2015, and contains approx. 150 million trades from 354,817 investors.

3.3 Are Traders with a Large Disposition Effect Attractive?

Our results (see Section 3.2) suggest that leader traders are more susceptible to the disposition effect than autonomous traders. Thus, either being susceptible to the disposition effect is an attractive feature that increases the likelihood of an investor to be followed by other traders, or investors that are being followed become more susceptible towards the disposition effect. In this section, we study whether investors that are susceptible to the disposition effect are more likely to increase their number of followers.

Pelster (2017) and Röder and Walter (2017) document that in social trading portfolios the likelihood to adopt the strategy of another investors is momentum-driven and increases in its past returns. Moreover, Pelster (2017) shows that the likelihood to increase ones audience is significantly correlated with a trader's past variance of returns. This is consistent with the social transmission bias (see Han and Hirshleifer, 2016). Our results suggest that the probability to increase one's audience may also be explained by the disposition effect.

We estimate probit regression models using a dummy variable that takes the value of one if the change in the number of followers is positive in a given week, zero otherwise, as our dependent variable. We lag explanatory variables by one period. Marginal effects of our estimations are presented in Table 5. While the coefficient on the disposition effect is significantly different from zero, the economic impact is extremely small. Thus, being more susceptible to the disposition effect does not meaningfully increase one's likelihood to gain additional followers.

Variable	Marginal effect
Disposition effect	0.008
	(0.000)
Avg. ROI	1.204
	(0.028)
SD ROI	0.382
	(0.017)
Avg. holding period	-0.002
	(0.000)
Avg. investment	0.000
	(0.000)
Avg. leverage	0.000
	(0.000)
No. instruments	0.001
	(0.000)
Observations	3,410,610
No. of Traders	156,246
Chi^2	5,015.2
Pseudo R^2	0.02

Table 5: Probability that investors will increase their audience (marginal effects)

The table reports the marginal effects of our probit regressions. The dependent variable is a dummy variable taking value one if the investor increases her audience in a given week. Standard errors reported in parentheses are clustered at the individual investor level to mitigate possible issues due to heteroskedasticity and serial correlation. As standard errors in the multivariate regression framework decrease in sample size, the dimensions of our sample will yield statistically significant results beyond conventional levels of significance. In light of this observation, we focus on the economic significance and present marginal effects. Data on trading behavior are from eToro. In total, our sample runs from January 1, 2012, to October 8, 2015, and contains approx. 150 million trades from 354,817 investors.

3.4 Do Newly Appointed Leaders Change Their Trading Behavior?

While leader traders exhibit a significantly larger disposition effect than traders that are not being followed by other investors, the probability of an investor to increase the number of investors that follow her investment decisions does not meaningfully increase in the disposition effect. This suggests that investors change their trading behavior when they are followed by other investors. In the following, we test whether investors' propensity towards the disposition effect increases when they are followed by other traders for the first time. In order to identify whether leader traders change their behavior after becoming a leader, a difference-in-differences approach is used.

Our treatment group consists of investors that are followed by another trader for the first time. We compare the disposition effect of these investors before and after treatment (which is the event of being followed for the first time) with those of a control group. In this control group, we do not include all other investors;

rather, we employ a nearest neighbor matching strategy to find traders with similar trading strategies.[11] After-matching comparison of the characteristics of treated and non-treated investors shows that the two groups do not differ significantly in their features.

Table 6 presents the results of our analysis. We observe that the coefficient on the treatment is positive and significantly different from zero, both statistically and economically. This finding suggests that investors indeed are more susceptible towards the disposition effect when they are followed by other investors. After being followed for the first time, investors are less likely to close losing positions; their disposition effect increases.

We offer the following possible explanations for the observed behavioral bias.

1. Leaders may feel a sense of responsibility for their followers. Leader traders may believe that they let their followers down when they close a losing position, and thus accept the loss for their followers. Therefore, investors may become more susceptible to the disposition effect once they are leaders.
2. Leaders may fear that their followers are disappointed by the loss and consequently terminate the leader-follower relationship. As a consequence, traders that become a leader for the first time display an increased vulnerability for the disposition effect.
3. The change in investment behavior of leaders may also display their desire to manage their self-image. The importance of impression-management strategies in the context of financial performance disclosure to clients has been previously discussed in the financial literature, e.g. in the context of professional fund managers or loan officers (Lakonishok et al., 1991; Hertzberg and Paravisini, 2010). Similarly, Heimer (2016) discusses impression-management in a disposition effect context for investors that trade open to the public. Our paper takes this a step further and shows the increased urge to manage one's self-image for (unprofessional) financial advisors providing peer-to-peer advice. Leaders may decide to keep their losing positions open in order to signal confidence in their initial investment decision. Closing the position signals a bad investment decision. However, keeping the position open signals that the leader still believes in his initial decision and is confident that the security will increase in value.

4 Extensions

4.1 Escalation of Commitment

When newly appointed leader traders engage in impression management and hold on to losing positions in order to signal confidence in their investment choices they may even choose to increase their positions. By

[11] Control traders are matched based on the following covariates before the treatment event: their disposition effect, the average number of trades per week, the average holding period, the average investment, the number of different instruments they trade, the average leverage, the number of followed traders, and the average profitability. These restrictions ensure that the control traders are relatively similar to the treated ones. Treated investors for which we do not find a control trader are not considered in the following analysis.

	Disposition effect
(Intercept)	0.12
	(0.01)
Treatment	0.05
	(0.00)
No. trades	-0.00
	(0.00)
Avg. ROI	4.76
	(0.48)
Avg. Leverage	-0.00
	(0.00)
Avg. holding period	0.03
	(0.00)
Diversification	0.19
	(0.00)
No. followed traders	0.02
	(0.00)
No. instruments	-0.00
	(0.00)
R^2	0.18
Adj. R^2	0.18
Num. obs.	51,182
RMSE	0.33

Table 6: The disposition effect of new leader traders

The table reports the results of our difference-in-differences estimations of the disposition effect of investors of the social trading platform around the week that they are followed by another trader for the first time. Non-treated investors are matched based on covariates characterizing the trading behavior. Standard errors are reported in parentheses.

increasing an existing, losing position, leaders are able to signal an even higher confidence level to their followers. Moreover, from a rational point of view, the increasing of an losing position promises even higher returns if the initial assessment of the investment choice was correct. Therefore, in this section, we discuss investors' inclination towards escalation of commitment.

In an extension of the disposition effect, Odean (1998) finds that investors purchase additional shares of stocks with a paper loss relatively more often than shares of stocks with a paper gain. He argues that decreased risk aversion after a loss and increased risk aversion after a gain is responsible for this behavior.[12] In the psychological literature, this type of behavior is well documented under the term *escalation of commitment* (Staw, 1997). Brockner (1992) explains this behavior with the value function from Prospect Theory.

[12] 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.

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.[13]

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).[14]

We begin our analysis on the probability of increasing positions by presenting descriptive statistics. Figure 4 shows the fraction of increased positions by trade groups. Panel (a) shows all traders. Across all trade groups, non-profitable trades are increased more often than profitable trades. Yet, across all trade groups, approx. 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 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 have more followers exhibit a higher propensity to increase profitable positions.

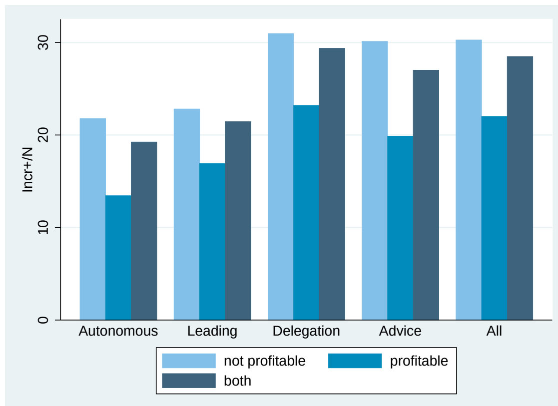
Panel (b) [(c)] shows the fraction of increased positions for winning [losing] traders. Notably, losing traders show a higher fraction of increased positions than do winning traders across all trade groups.

Next, Figure 5 presents the profitability of increased and non-increased positions. Consistent with our previous observations, the average ROI across all trades is significantly negative.[15] We observe that for all trades, non-increased positions have a smaller ROI than increased positions. However, autonomous and advice 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 5 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 autonomous trades is significantly more pronounced than for any other trade group. Panels (d) and (e) of Figure 5 present the ROIs for winning

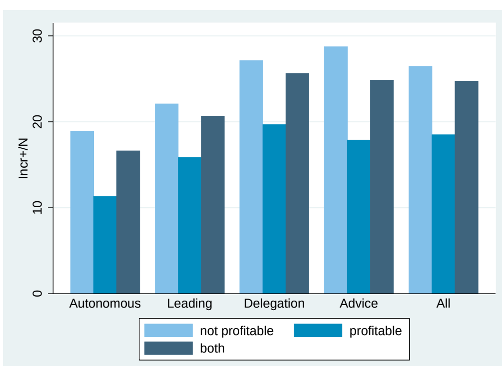
[13] Note that a different explanation for escalation of commitment is the *self-justification hypothesis* proposed by Staw (1976). He argues that individuals maintain a course of action because they feel the need to justify their initial decisions. Consistent with self-justification, investors could perceive a price decrease as a good buying opportunity (Weber and Camerer, 1998). It 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.

[14] Weber and Zuchel (2005) study both the house-money effect and escalation of commitment in an experimental setting. They 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. Conversely, when the problem is presented as a two-stage lottery, participants' behavior shows greater risk-taking following gains, consistent with the house-money effect. To date, there is no evidence on how the social interaction on a trading platform may influence investor behavior.

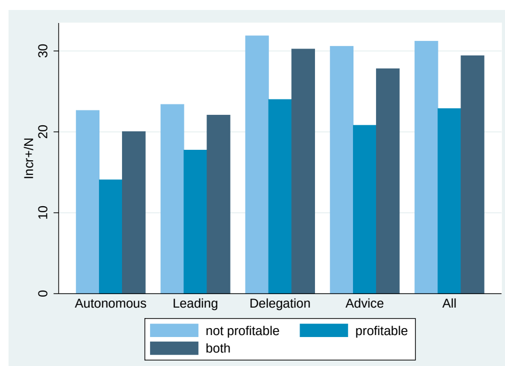
[15] Note that the reported ROI differs from the previously reported values, as our analysis in this section is restricted to trades that were opened and closed on different trading days.



(a) All traders



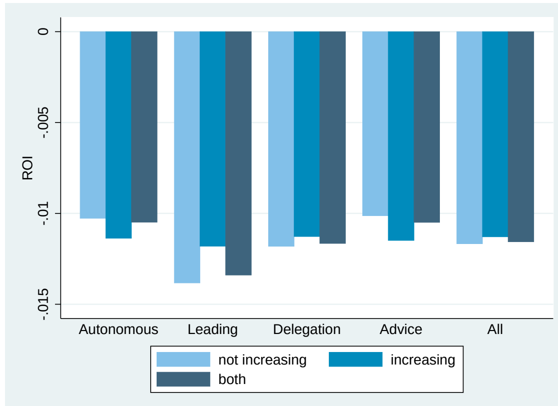
(b) Winning traders



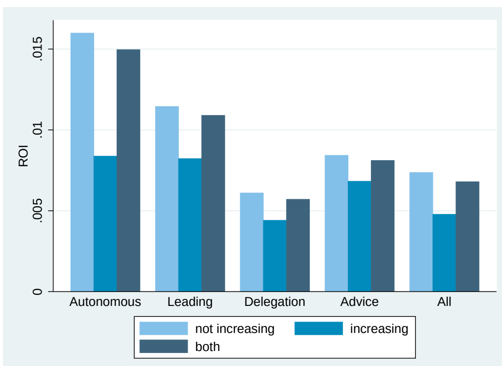
(c) Losing traders

Figure 4: Fraction of increased positions

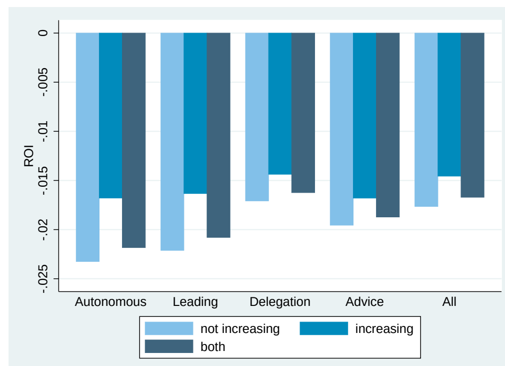
The figure shows the fraction of increased positions by trade groups. Panel (a) shows all traders, while Panel (b) [(c)] is restricted to winning [losing] traders. Each panel is divided into profitable and non-profitable trades. Data on trading behavior are from eToro. This figure is based on a subsample of our data, covering the year 2012 which contains 26.5 million trades from 79,922 investors.



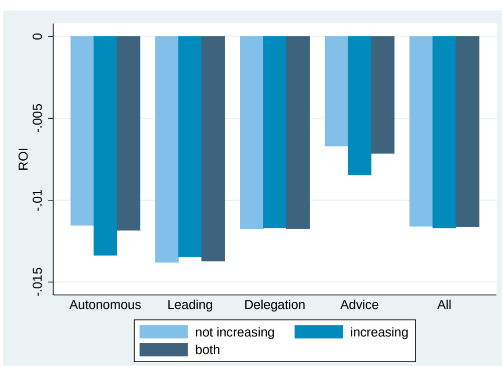
(a) All trades and traders



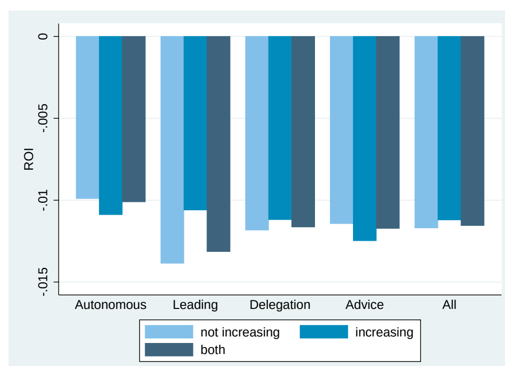
(b) Profitable trades



(c) Losing trades



(d) Winning traders



(e) Losing traders

Figure 5: 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. This figure is based on a subsample of our data, covering the year 2012 which contains 26.5 million trades from 79,922 investors.

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 expect that losing trades are more likely to be increased than winning trades. This tendency should be less pronounced for leader trades, as leader trades seem to be increased more often for profitable trades than autonomous trades. Moreover, for leader trades, we expect the audience to alter the propensity of investors to increase their position. We argue that by increasing a losing position, investors want to signal confidence in their initial investment decision to their followers. Thus, we expect that losing trades' propensity to be increased is especially large for trades with many followers.

We model the probability of increasing existing positions, again using probit regression analysis. 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 3.2. Additionally, we introduce `Losing trade` variables for each trade group, similar to the `Profitable trade` variables above. Formally, we estimate the following model:

$$\Pr(\texttt{increase})_{it} = \sum_{i} \texttt{Losing\ \ trade}_{it} \times \texttt{Trade\ \ group}_{i} + \texttt{Followers}_{it} + \texttt{Controls}_{it} + \epsilon_{it}.$$

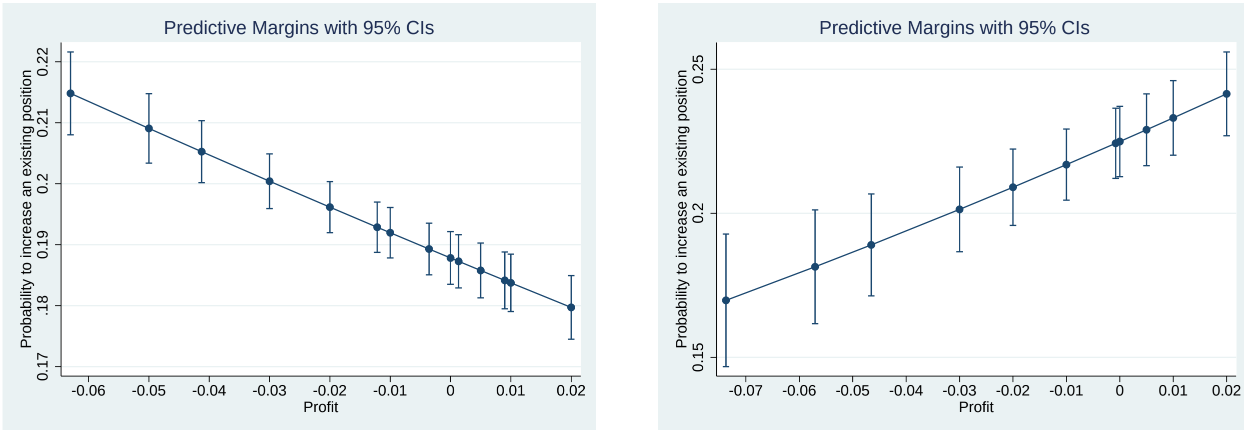
Again, we show marginal effects to account for the large size of our sample and focus on economic significance. To confirm the generality of our results, a repetition of our main analysis with smaller subsamples of equal group size in a bootstrapping exercise strongly supports our results (see below). The marginal effects of our estimations are presented in Table 7. As expected, across all groups, the probability of increasing an existing position is higher for losing trades. While autonomous trades are approx. 12.7% more likely to be increased if the position is losing, this value is significantly smaller for social trades (approx. 9% for delegation trades and 10.1% for advice trades). Leader trades show the lowest marginal effect at approx. 7.7%. At first glance, the number of followers (`Followers`) does not seem to have any meaningful influence on the probability of increasing an existing position (Model 2).

In Models 3-4, we replace our dummy variables denoting losing trades with a continuous variable capturing the current paper gains of an existing position. Model 3 highlights the group differences observed in Figure 5. While the propensity to increase an existing position decreases with the paper profits of a trade for autonomous and advice trades, the opposite is true for leader and delegation trades. Leader trades are particularly more likely to be increased in the presence of paper profits. The group differences between autonomous and leader trades are displayed in Figure 6. Panel (a) shows the decreasing probability (with confidence intervals) for autonomous trades, and Panel (b) highlights the increasing probability with increasing paper profits. While losing positions have an approx. 21.5% chance of being increased, this probability decreases for winning trades to approx. 18%. Leader traders, by contrast, are more likely to increase a position when the existing position is winning. The observed differences between Models 1 and 3 for leader and delegation trades are consistent with the large differences in ROI between increased and non-increased positions displayed in Figure 5. 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.

	(1)	(2)	(3)	(4)	(5)
Losing trade, autonomous trades	0.127				
	(0.003)				
Losing trade, leader trades	0.077	0.064			
	(0.008)	(0.007)			
Losing trade, delegation trades	0.090				
	(0.001)				
Losing trade, advice trades	0.101				
	(0.003)				
Profit, autonomous trades			-1.257		
			(0.073)		
Profit, leader trades			0.724	0.678	2.142
			(0.211)	(0.190)	(0.227)
Profit, delegation trades			0.097		
			(0.036)		
Profit, advice trades			-0.767		
			(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	-0.067	-0.087	-0.069	-0.065
	(0.001)	(0.008)	(0.001)	(0.009)	(0.009)
Leader trade	0.047		0.039		
	(0.009)		(0.007)		
Delegation trade	0.120		0.116		
	(0.003)		(0.003)		
Advice trade	0.127		0.112		
	(0.006)		(0.005)		
Observations	80,696,684	1,094,476	80,696,684	1,094,476	1,094,476
No. of Traders	75,832	6,936	75,832	6,936	6,936
Wald Chi^2	32,788	279.5	16,960	171.3	427.4
Pseudo R^2	0.02	0.01	0.02	0.01	0.02

Table 7: Probability that investors will increase an existing position (marginal effects)

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. As standard errors in the multivariate regression framework decrease in sample size, the dimensions of our sample will yield statistically significant results beyond conventional levels of significance. In light of this observation, we focus on the economic significance and present marginal effects. Data on trading behavior are from eToro. This table is based on a subsample of our data, covering the year 2012 which contains 26.5 million trades from 79,922 investors. Additionally, we repeat our main analysis with smaller subsamples of equal group size in a bootstrapping exercise and present the results in Table 8.



(a) Autonomous trades

(b) Leader trades

Figure 6: 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 7 evaluated at different values of `Profit` . Panel (a) shows marginal effects for autonomous trades, while Panel (b) shows marginal effects for leader trades. Data on trading behavior are from eToro. This figure is based on a subsample of our data, covering the year 2012 which contains 26.5 million trades from 79,922 investors.

Model 4 suggests that the number of followers does not generally seem to have any meaningful influence on the probability of increasing an existing position. However, as argued above, investors are likely to react differently to their audience depending on the profitability of their trades. While positive returns are always welcome and may not alter the trading behavior if the leader has many followers, the opposite is likely to hold for negative returns. In the event that the leader opened a position that now reports paper losses, s/he has to justify this decision to his or her followers. We hypothesize that leaders make use of the possibility to increase their position in this case. We argue that, in these cases, leaders use the position increase as a signal to demonstrate their confidence in their initial investment decision. Investors are unwilling 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 ones' own trading abilities and reinforces the belief in favorable future market movements. Additionally, leaders benefit from the lower entry price of the security. To distinguish between profitable and losing trades, we again split the `Follower` variable (Model 5) and find evidence in support of our hypothesis. We observe significant differences between winning and losing positions. 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. 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 investors copying their investment strategies.

Table 8 presents the bootstrapping analysis on the probability that investors will increase existing positions. Again, we randomly draw 10,000 observations from each group and estimate Model 1 of Table 7. We repeat this exercise 5,000 times and present summary statistics of the resulting distribution in Table 8. Although the marginal effects again differ slightly from our main analysis, the substance of our results is confirmed. Marginal effects are significant in an economically relevant magnitude and vary across trade groups.

Variable	Obs	Mean	SD	Min.	Max.	P5	P95
Profitable trade, autonomous trades							
Marginal effect	5,000	.107	.01	.071	.147	.091	.124
t statistic	5,000	10.277	.913	6.946	13.96	8.8	11.777
Profitable trade, leader trades							
Marginal effect	5,000	.073	.011	.039	.111	.056	.091
t statistic	5,000	5.706	.874	2.894	9.26	4.309	7.161
Profitable trade, delegation trades							
Marginal effect	5,000	.08	.01	.039	.113	.063	.097
t statistic	5,000	7.685	.948	3.937	10.634	6.088	9.24
Profitable trade, advice trades							
Marginal effect	5,000	.105	.009	.069	.138	.09	.121
t statistic	5,000	10.762	.935	7.216	14.454	9.245	12.292

Table 8: Summary Statistics of Bootstrapping Exercise: Probability that Investors will Increase an Existing Position (Marginal Effects)

The table shows summary statistics of the distributions of our main variables of interest that result from repeatedly ($N = 5,000$) drawing random samples from our dataset and estimating probit regressions. We randomly draw 10,000 observations from each group and estimate Model (1) from Table 7. Data on trading behavior are from eToro. In total, our sample runs from January 1, 2012, to October 8, 2015, and contains approx. 150 million trades from 354,817 investors.

4.2 The Realization Effect

The realization effect (Imas, 2016) reconciles the apparent contradiction between escalation of commitment and the house-money effect by stating that individuals avoid risk following a realized loss but take on greater risk if the loss is not realized and only a loss on paper. Imas (2016) documents that realized losses and paper losses influence investment behavior in different ways. In line with his results, one expects here that traders will decrease their risk-taking following a realized loss. Moreover, one would expect that leader traders' reactions to realized losses will be especially pronounced, as they are seeking to retain followers. In order to test this hypothesis, Appendix A offers fixed effects panel regression results. Our findings differ from the experimental results presented by Imas (2016). We cannot confirm the realization effect in our individual trade data. In contrast, we find strong evidence that investors using a real-world trading platform do not seem to distinguish between paper losses and realized losses.

Interestingly, while investors tend to increase their risk-taking both after realized losses and after paper losses, results suggest that the increase in risk-taking is significantly larger for those investors whose trading behavior is imitated by other investors. It seems that these investors are especially concerned about their trading performance and enter highly risky positions in an effort to relatively quickly improve their trading performance, an indicator of fear of reputational loss.

4.3 FX Investors vs. Stock Market Investors

It seems noteworthy that foreign exchange securities represent the major part of the data, and thus our conclusions might largely be valid for these investment strategies only.[16] Foreign exchange investors may follow different investment patterns than stock market investors as these markets are fundamentally different from each other. This is supported by ter Ellen et al. (2017) who find evidence for behavioral heterogeneity in several asset classes, but not in equities. For example, foreign exchange traders view private information as an important feature of their market (King et al., 2013), and the feeling of having private information in social interactions and other investor emotions have been shown to be decisive factors in financial decision-making processes (see, for instance, Au et al., 2003).

We repeat our analysis including only investors that have a focus on foreign exchange trading and only investors that focus on stock market trading, respectively. Our results suggest that—with regard to the disposition effect—we do not observe any notable differences between foreign exchange and stock market investors.[17]

5 Conclusions

This article studies the relationship between giving financial advice and the disposition effect in an online trading environment. Our large and unique dataset allows us to differentiate between different trader types: isolated (autonomous) traders, leaders (*investment advisers*), and *advice seekers* (delegation and advice traders).

Our empirical findings suggest a significant correlation between the number of investors 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 empirical findings suggest that leader traders are more susceptible to the disposition effect than investors that are not being followed by any other traders. Using a difference-in-differences approach, we show that becoming a financial advisor for the first time increases the disposition effect. This finding holds for investors who engage in foreign exchange trading as well as for investors who trade stocks and stock market indices. Our observation may be explained by leaders feeling responsible towards their followers and an urge to not let them down, by fear of losing followers when admitting a bad investment decision and signaling confidence in their initial investment choice, or by an attempt of newly appointed leaders to manage their self-image. Holding onto negative trades signals to their followers that they have confidence in their financial strategy and does not adversely affect their realized performance or ranking because unrealized losses are not reflected in their end returns. Thus, our results suggest that the disposition effect is boosted by the fear of reputational loss when leader traders are observed by their peers.

Our findings demonstrate that advice seekers need to monitor newly appointed advisors closely as they may change their investment behavior. The observed investment activities before the leader-follower relationship

[16]Note that foreign exchange trades represent a significant part of trades all over the world.
[17]We do not tabulate the results here in order to preserve space.

is established do not guarantee a similar investment behavior in the future. Previous activities do not account for the possible changes in behavioral biases after an investor is followed for the first time.

Based on the insights in this paper, newly appointed investment advisors may try to uncouple from their biases when they understand that they are susceptible to them. Awareness of these insights from risk psychology and behavioral finance may considerably improve the efficiency and rationality of financial advisors acting in an interdependent network. This study highlights the importance of understanding the behavioral biases when offering financial advice.

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Appendix A - Realization Effect

For our analysis we rely on the aggregated individual trade data at the trader level on a weekly basis. We determine the performance of all trades realized in the previous week. We drop all trader-month observations with no or ambiguous previous experience and create a dummy variable `Realized losses` that equals one if the investor closed a position at a loss in the previous week and zero if the investor closed a position with a gain.[18] We restrict our analysis sample to the year 2012, which results in 287,209 trader-week observations.

For each trader-week, we determine the average `Leverage` across all positions opened in a given week. We exploit the changes in this variable to account for the change in the risk-taking behavior of investors. We compare the change in the `Leverage` of investors' positions after realized gains and losses. Figure 7 presents the results of our analysis separated by groups and for all groups together. Across all groups, we observe significant increases in risk-taking after realized losses. Note that all differences between groups are statistically significant as indicated by t-tests. In contrast, after realized gains, autonomous 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 extent 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 t-tests. Interestingly, the increase in risk-taking is significantly more pronounced for leader and social traders. We argue that leader traders have additional incentives to increase their risk-taking after realized losses to smooth their overall performance and retain their followers. This increased risk-taking is transferred to the group of social traders by means of the following function presented in Figure 7.

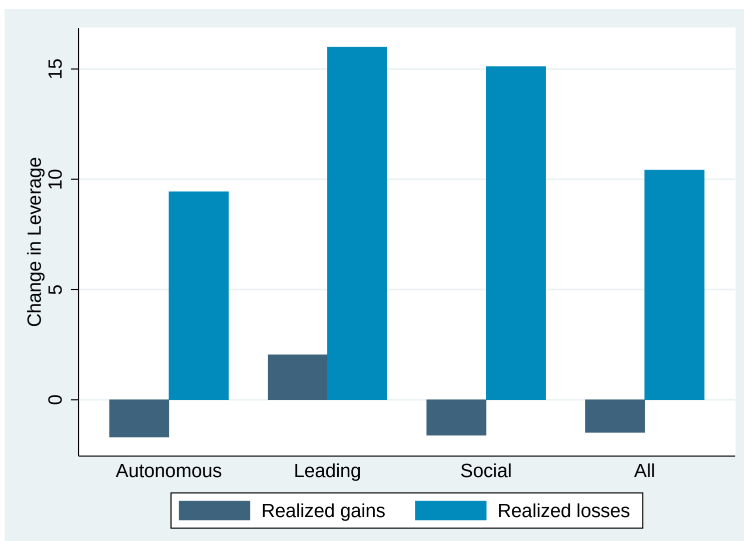


Figure 7: Risk-taking behavior after realized gains or losses

The figure shows the change in the `Leverage` of investors after realized gains or losses. `Leverage` denotes the average leverage of positions opened by investors in a week. Data on trading behavior are from eToro. This figure is based on a subsample of our data, covering the year 2012 which contains 26.5 million trades from 79,922 investors. Aggregated at a weekly frequency, our dataset contains 287,209 trader-week observations. Aggregated at a weekly frequency, our dataset contains 287,209 trader-week observations.

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

To confirm the descriptive results in a multivariate setting, we estimate panel regressions with time fixed and trader fixed effects to control for unobserved factors and analyze the influence of realized losses on risk-taking for our different trader groups. Based on our univariate results, we expect that investors increase their risk-taking after a loss. This effect should be more pronounced for leader traders because of their effort to improve their trading performance statistics. Formally, we estimate regressions of the following form for each group:

$$\Delta\texttt{Leverage}_{i,t} = \beta_1 \cdot \texttt{Realized\ \ losses}_{i,t} + \sum_{j=2}^{J} \beta_j \cdot \texttt{Controls}^j_{i,t} + \sum_{k=1}^{K} \gamma_k \texttt{Year\_}(k)_t + \sum_{n=1}^{N} \iota_n \texttt{Trader\_}(n)_i + \epsilon_{i,t}$$

Standard errors are clustered at the investor level.[19] As additional control variables, we include, depending on the type of investor that we investigate, the number of non-social (autonomous) trades, the number of social trades, the average number of instruments, the average holding period, the number of followers for trades opened in the week, the number of traders copied (manually or automatically) on trades in that week, and our diversification proxy. Finally, we calculate different ratios capturing the fraction of leader trades and the fraction of delegation trades for each investors in a given week. The results of our panel regressions are presented in Table 9. Model 1 only includes autonomous traders. `Realized  losses` enters the model with a significantly positive coefficient, underlining finding that investors increase their risk-taking after previous realized losses. Models 2 and 3 contain data on leader and social traders, respectively. In line with Figure 7, the coefficient on `Realized  losses` is significantly larger for these trader groups when compared to non-social traders.[20]

Finally, we perform a bootstrapping exercise on our analysis of risk-taking behavior after realized gains and losses. For each group, we randomly draw 50,000 trader-week observations and estimate Models 1-3 from Table 9. We repeat this exercise 10,000 times and present summary statistics of the resulting distributions in Tables 10-12. The means of the coefficients are close to the coefficients documented in Table 9, and the average t-statistics confirm our levels of statistical significance. In fewer than 5% of our subsamples, the coefficients are not statistically significant.

[19] Note that, as standard errors in the multivariate regression framework decrease in sample size, the dimensions of our sample will yield statistically significant results beyond conventional levels of significance. In light of this observation, an asterisk denotes statistically significant coefficients obtained from a bootstrapping exercise.

[20] We repeated our analysis with randomly selected subsamples which confirms the generality of our results.

	(1)	(2)	(3)
Realized losses	7.306*	9.796*	9.799*
	(13.266)	(6.765)	(18.387)
No. autonomous trades	0.219*	0.110*	
	(14.296)	(5.744)	
No. instruments	-0.251	-0.326*	-0.208
	(-3.406)	(-3.583)	(-6.502)
Diversification	0.168	1.149	1.895
	(0.195)	(1.142)	(4.919)
Avg. investment	-0.049	-0.215*	-0.001
	(-1.414)	(-3.289)	(-0.055)
Avg. holding period	-0.012*	-0.013*	-0.021*
	(-20.577)	(-9.739)	(-29.569)
Leader trades ratio		10.953*	
		(7.474)	
Number of followers		0.001	
		(0.496)	
Delegation trades ratio			-37.830*
			(-43.435)
No. social trades			0.027*
			(15.067)
No. followed traders			0.336
			(7.123)
Constant	8.715	8.428	53.794
	(5.103)	(2.327)	(41.659)
Trader fixed effects	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes
Observations	291,616	56,980	361,553
No. of Traders	45,070	10,789	31,574
F-Test	44.4	14.4	228.5
Adj. R^2	0.017	0.032	0.105

Table 9: Risk-taking behavior after realized gains or losses

The table reports the results of our fixed effects panel regressions. The dependent variable is the change in the average `Leverage` of a trader across all trades opened in a week. Column 1 (2 / 3) contains data on autonomous traders (leader traders / social traders). Standard errors are clustered at the individual investor level to mitigate possible issues due to heteroskedasticity and serial correlation. *t*-statistics are in parentheses. As standard errors in the multivariate regression framework decrease in sample size, the dimensions of our sample will yield statistically significant results beyond conventional levels of significance. In light of this observation, an asterisk denotes statistically significant coefficients obtained from a bootstrapping analysis (see Tables 10, 11, and 12). Data on trading behavior are from eToro. This table is based on a subsample of our data, covering the year 2012 which contains 26.5 million trades from 79,922 investors. Aggregated at a weekly frequency, our dataset contains 287,209 trader-week observations.

Appendix B - Investor's performance on the social trading platform

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 8 illustrates the winning percentage distribution, $P(w)$, which is clearly asymmetrically distributed around one-half. Approx. 85% of the w values have a value greater than one-half, meaning that most investors have a higher share of positive trades. Most of the 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.

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 9. 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 approx. 45% of all u values. Approx. 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.

Variable	Obs	Mean	SD	Min.	Max.	P5	P95
Realized losses							
Coefficient	10,000	7.496	1.632	.405	13.31	4.815	10.215
t-statistic	10,000	4.37	.948	.227	7.67	2.814	5.936
No. autonomous trades							
Coefficient	10,000	.184	.036	.049	.338	.126	.243
t-statistic	10,000	4.799	.839	1.354	8.343	3.389	6.164
No. instruments							
Coefficient	10,000	-.262	.199	-1.09	.605	-.594	.065
t-statistic	10,000	-1.265	.961	-5.341	3.008	-2.862	.313
Diversification							
Coefficient	10,000	-1.208	1.834	-8.044	5.594	-4.165	1.865
t-statistic	10,000	-.672	1.049	-4.493	3.154	-2.351	1.104
Avg. investment							
Coefficient	10,000	-.12	.06	-.323	.019	-.216	-.006
t-statistic	10,000	-2.435	1.117	-6.631	1.316	-4.274	-.586
Avg. holding period							
Coefficient	10,000	-.01	.001	-.016	-.004	-.013	-.008
t-statistic	10,000	-7.073	1.309	-10.913	-2.032	-8.941	-4.508

Table 10: Summary statistics of bootstrapping exercise: Realized priors (Autonomous)

The table shows summary statistics of the distributions that result from repeatedly ($N = 10,000$) drawing random samples from our dataset and estimating fixed effect regressions as documented in Section 5. We randomly draw 50,000 observations from each group and estimate Model (1) from Table 9. Data on trading behavior are from eToro. In total, our sample runs from January 1, 2012, to October 8, 2015, and contains approx. 150 million trades from 354,817 investors.

Variable	Obs	Mean	SD	Min.	Max.	P5	P95
Realized losses							
Coefficient	10,000	6.032	.38	4.692	7.522	5.405	6.66
t-statistic	10,000	3.087	.19	2.447	3.831	2.778	3.405
Leader trades ratio							
Coefficient	10,000	6.89	.485	5.074	8.78	6.099	7.701
t-statistic	10,000	3.435	.232	2.572	4.353	3.056	3.823
No. autonomous trades							
Coefficient	10,000	.074	.003	.061	.087	.068	.08
t-statistic	10,000	3.549	.095	3.201	3.932	3.396	3.707
No. instruments							
Coefficient	10,000	-.606	.062	-.843	-.398	-.707	-.504
t-statistic	10,000	-3.318	.325	-4.446	-2.192	-3.851	-2.785
Diversification							
Coefficient	10,000	4.702	.382	3.219	6.125	4.074	5.343
t-statistic	10,000	2.823	.229	1.965	3.671	2.449	3.205
Avg. investment							
Coefficient	10,000	-.377	.015	-.435	-.323	-.402	-.352
t-statistic	10,000	-4.708	.199	-5.584	-4.027	-5.042	-4.386
Avg. holding period							
Coefficient	10,000	-.009	0	-.009	-.007	-.009	-.008
t-statistic	10,000	-6.256	.159	-6.885	-5.669	-6.522	-5.998
Number of followers							
Coefficient	10,000	0	0	-.001	.001	-.001	0
t-statistic	10,000	-.124	.209	-1.47	.524	-.515	.175

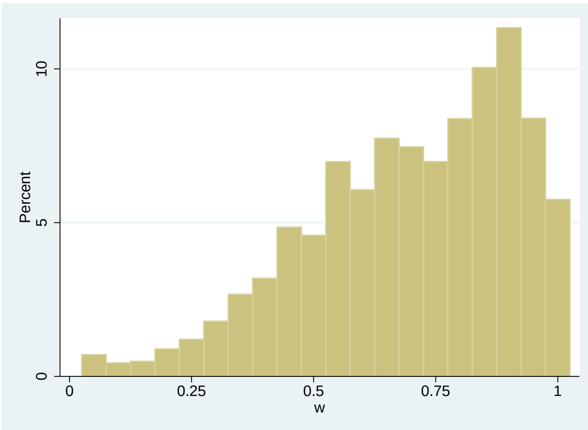
Table 11: Summary statistics of bootstrapping exercise: Realized priors (Leader)

The table shows summary statistics of the distributions that result from repeatedly ($N = 10,000$) drawing random samples from our dataset and estimating fixed effect regressions as documented in Section 5. We randomly draw 50,000 observations from each group and estimate Model (2) from Table 9. Data on trading behavior are from eToro. In total, our sample runs from January 1, 2012, to October 8, 2015, and contains approx. 150 million trades from 354,817 investors.

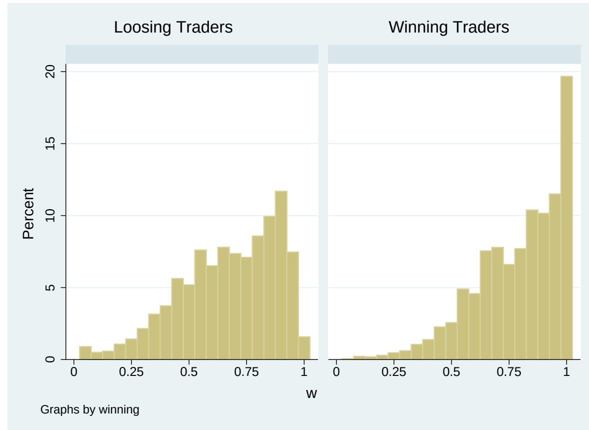
Variable	Obs	Mean	SD	Min.	Max.	P5	P95
Realized losses							
Coefficient	10,000	8.784	1.718	2.071	15.387	5.98	11.654
t-statistic	10,000	4.899	.967	1.144	8.449	3.326	6.497
Delegation trades ratio							
Coefficient	10,000	-30.942	3.148	-42.43	-19.278	-36.114	-25.835
t-statistic	10,000	-9.426	1.078	-13.229	-5.28	-11.244	-7.671
No. social trades							
Coefficient	10,000	.027	.005	.006	.047	.019	.035
t-statistic	10,000	5.238	1.053	.618	9.4	3.467	6.964
No. instruments							
Coefficient	10,000	-.249	.099	-.625	.117	-.413	-.086
t-statistic	10,000	-2.399	.956	-6.107	1.173	-3.999	-.83
Diversification							
Coefficient	10,000	1.931	1.33	-3.04	7.097	-.276	4.112
t-statistic	10,000	1.406	.968	-2.141	5.146	-.202	2.995
Avg. investment							
Coefficient	10,000	-.067	.151	-.719	.709	-.328	.175
t-statistic	10,000	-.125	1.615	-4.63	8.886	-2.221	3.287
Avg. holding period							
Coefficient	10,000	-.019	.002	-.028	-.011	-.023	-.016
t-statistic	10,000	-8.946	.941	-12.777	-4.946	-10.493	-7.415
No. followed traders							
Coefficient	10,000	.264	.148	-.287	.835	.019	.509
t-statistic	10,000	1.727	.972	-1.836	5.058	.124	3.312

Table 12: Summary statistics of bootstrapping exercise: Realized priors (Social)

The table shows summary statistics of the distributions that result from repeatedly ($N = 10,000$) drawing random samples from our dataset and estimating fixed effect regressions as documented in Section 5. We randomly draw 50,000 observations from each group and estimate Model (3) from Table 9. Data on trading behavior are from eToro. In total, our sample runs from January 1, 2012, to October 8, 2015, and contains approx. 150 million trades from 354,817 investors.



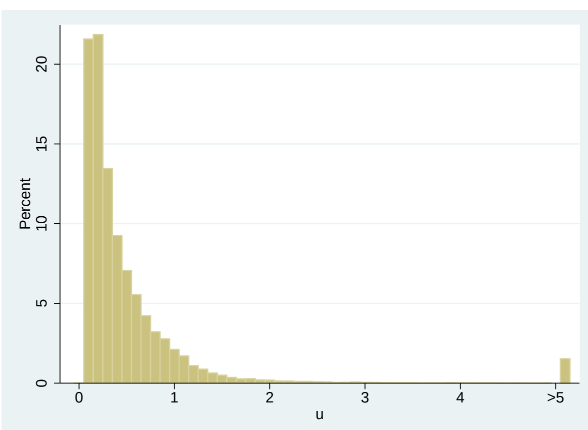
(a) Winning percentage: all traders



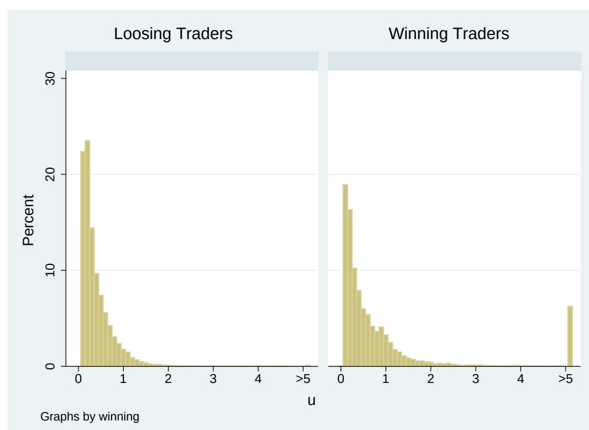
(b) Winning percentage winning vs. losing traders

Figure 8: 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. This figure is based on a subsample of our data, covering the year 2012 which contains 26.5 million trades from 79,922 investors.



(a) Win-loss ROI: all traders



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

Figure 9: 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) separately reports the distribution for losing and winning traders. Data on trading behavior are from eToro. This figure is based on a subsample of our data, covering the year 2012 which contains 26.5 million trades from 79,922 investors.