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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 who are not being followed by any other trader. Using a difference-in-differences approach, we show that becoming a first-time financial advisor increases the disposition effect. This finding holds for investors who engage in foreign exchange trading and for investors who trade stocks and stock market indices. The increased behavioral bias may be explained by leaders feeling responsible to their followers, by a fear of losing followers when admitting a poor investment decision, or by an attempt by newly appointed leaders to manage their social image and self-image.

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1. Introduction

Social trading is a novel way to participate in financial markets. In the past, financial market participants 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 entry barriers. In addition, these online platforms allow investors to interact with one another and view other investors' trading activities. Investors can easily observe the trading behavior of their peers and replicate trading strategies by others, without the help of a professional broker. Even 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 platforms is the traders' ability to copy other platform users, which can be done manually (*advice trading*), or automatically (*delegation trading*).[1] We use this copy feature of social trading to categorize investors into four types, according to their degree of social interaction: investors who (i) manually duplicate the investment strategies of other traders

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[1] Although copy traders 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 can be called such because the management of the portfolio is, in a sense, delegated (Doering et al., 2015). Note that leader traders—the signal providers whose investment strategies are duplicated by other traders—receive a payment for sharing their trading strategies. The amount of money received varies with the number of followers, the platform type, and the success of trading strategies. In this sense, social trading platforms can be seen as potential substitutes for common asset management services; they facilitate access to financial markets for traders outside the financial sector.

("advice traders"), (ii) automatically duplicate the investment strategy of one or more selected other investors ("delegation traders"), (iii) have their investment strategies copied by other investors ("leader traders"), and (iv) execute trades on their own without copying other investors or being copied ("autonomous traders"). Then, we investigate whether investment behavior differs significantly across these trader types. In particular, we study whether leader traders significantly differ from autonomous investors with respect to their *disposition effect*—i.e., the tendency of investors to forego loss realization in favor of gain realization.[2] We study whether investors increase their disposition effect once they become leaders.

Social trading may alter investors' behavior. Recent literature provides convincing evidence that investors tend to value the advice of non-expert friends before making financial decisions (Van Rooij et al., 2011; Qin, 2012). Heimer (2016) shows that for investors who trade open to the public, the disposition effect tends to be higher than in a common trading setting without any social interactions among traders and reasons that impression management contributes to the disposition effect. He argues that social investors' strategic efforts to convey a positive image may increase their disposition effect, stating that *the appearance of success enables more socially persuasive interaction with others*. In line with the social transmission theory by Han et al. (2017), he argues that *traders value the option to recount victories and seek to report positively about themselves*. In contrast, with a losing position in their portfolio, traders not only have to admit failure to themselves but also to their peers. As a result, Heimer (2016) argues that *financial peer effects—like the disposition effect—asymmetrically relate to gains and losses.* This notion is supported by the contemporaneous experimental study of Hermann et al. (2017), who show that investors making investment decisions for others are significantly more susceptible to the disposition effect.[3]

While Heimer (2016) considers the trading behavior of investors who share their trading activity with other investors in general, our focus is on a specific group of traders in social trading, the (unprofessional) *financial advisors* or *leaders*—who provide peer-to-peer advice. We argue that investors who are being followed by their peers are most closely monitored by their peers and, therefore, have an increased urge to manage their social and self-image which increases their disposition effect.[4] Investors are often subject to limited attention and processing power (Hirshleifer and Teoh, 2003). Thus, investors are not able to observe the trading behavior of all their peers. However, some investors on social trading platforms have a large number of other investors that observe their investment decisions. We argue that investors will become especially concerned about their online reputation and their increased transparency, when other investors start to follow their trading activities.

Several psychological mechanisms may cause investors to increase their disposition effect once they become leaders. First, leaders may feel a sense of responsibility for their followers. Leaders may believe that they have failed their followers when they close a losing position, and by doing so need to accept a loss for their followers. Investors may thus become more susceptible to the disposition effect once they are leader traders. Second, leader traders may fear that their followers are disappointed by a loss and terminate the leader-follower relationship. This fear may increase their vulnerability to the disposition effect. Finally, first-time leaders may change their investment behavior in a desire to improve both their social and self-image. Indeed, as argued by Elster (2009), feelings such as guilt and shame are associated with worse social and self-image, respectively. Leaders may decide to keep their losing positions open to signal confidence in their initial investment decisions. Burks et al. (2013) note that (over)confidence may be driven by the desire to send positive signals to others about one's own skill. Closing a losing position signals a bad investment decision. However, keeping the position open signals that the leader still believes in her initial decision and is confident that the security will increase in value. Thus, an investor who is being followed by other investors may keep losing positions open as a result of a bias in judgment or strategic lying to manage her social and self-image.[5]

This article adds additional insight to the existing list of possible explanations for why investment advisors tend to be prone to the disposition effect. 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 answers the question whether leader traders are more prone to the disposition effect. Our results support the hypothesis that traders who are being followed by other investors are more susceptible to the disposition effect.

The paper is organized as follows. The next section describes the trading platform and the data and discusses summary statistics. Section 3 presents our main results by analyzing the trading behavior of different traders. 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.[6] Trading with eToro allows following and/or copying or replicating trades of other traders. The platform permits 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 varying between \$50 and \$300, depending on region, and leverage trades up to 400 times. eToro does not charge any explicit transaction fees but is compensated through a portion of the bid/ask spread of the trades its investors place.

eToro's most prominent feature is the option to *Open Book Trading*, meaning that investors can access other investors' trad-

[2] Under the disposition effect, investors tend to be reluctant to close losing positions (Weber and Camerer, 1998; Odean, 1998). The effect refers to the tendency of investors to sell winners too soon (risk aversion after gains) while holding losers too long (risk seeking after losses), consistent with Prospect Theory (Kahneman and Tversky, 1979; Tversky, 1992). Although Prospect Theory is often recognized as a potential 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).

[3] In particular, the authors measure investors' social-value orientation with the incentivized measure of Murphy et al. (2011) and find that especially inexperienced investors with a higher degree of social-value orientation exhibit a larger disposition effect when deciding on behalf of others. Similarly, Rau (2015) shows that the disposition effect is especially pronounced for teams (see also Cici, 2012).

[4] The effect may even be amplified since they have monetary incentives to stay leaders. A decrease in the number of followers reduces the compensation that investors who are followed receive from the trading platform. Note however that monetary compensation is not necessarily required for this behavior. Investors might wish to be followed because of intrinsic motivations (see, e.g., Frey, 1994).

[5] Impression-management strategies in the context of financial performance disclosure to clients are discussed, e.g., in the context of professional fund managers or loan officers (Lakonishok et al., 1991; Hertzberg et al., 2010).

[6] https://www.etoro.com/. eToro claims that "since 2007, eToro has consistently taken measures to ensure its platform makes online trading and investing accessible to anyone. By keeping a balance between giving easy access to beginners and improving upon important elements for more experienced traders, eToro has solidified itself as the world's leading social trading platform."

ing information. The platform offers full trading transparency. Each user's current portfolio, full track record, risk score, and success/failure ratio are available for all users to see. Traders can observe all current and past positions of others including their paper and realized returns. In particular, investors' trading information includes the investor's full trading history. Moreover, investors can observe the current portfolio of all other traders who trade *Open Book*. Note that, among other statistics, an investor's fraction of winning trades is displayed very prominently within this information.

Similar to other social trading platforms, traders on eToro can either manually or automatically duplicate the trading strategies of others. Traders can observe others and then copy trades that capture their interest. eToro also permits traders to trade passively, i.e. other investors' trades are automatically copied (*delegation* or *mirror trading*). To do so, traders must allocate a proportion of their equity (up to 100% or $500,000) to another investor they want to mirror. Followed traders are copied proportionally, meaning that if the followed trader risks 1% of her equity on a specific trade, then *eToro* will use exactly 1% of the trader's allocated equity to mirror that trade. Alternatively, a trader can manually copy trades of others with the click of a mouse (*advice trading*).

A copy trader (i.e., follower) must consider the following eToro rules: (1) The minimum amount to invest in one trader is $200. (2) The maximum amount s/he can invest in one trader is $500,000. (3) The maximum amount of traders s/he can copy simultaneously is 100. (4) The minimum amount for a copied trade is $1; trades below this amount will not be opened. (5) If s/he closes a copied trade manually, the funds from this position will be credited back to his or her copy balance (the amount allocated to copy that trader).[7]

Leader traders receive compensation by eToro for being followed. The compensation is based on a graduated scale with four levels and comprises three components. The three components are reduced transaction fees between 20% and 100% of the spreads, fixed monthly payments of up to $1,000, and, thirdly, a monthly payment of 2% of their assets under management. On the lowest level, leaders are compensated with 20% of the spreads, while on the fourth and highest level, leaders are compensated with 100% of the spreads and a fixed monthly payment of $1,000 plus 2% of their assets under management.

Our dataset consists of all trades that took place on eToro between January 1, 2012 and October 8, 2015. The dataset contains all trades of traders who executed at least five trades during the sample period. In total, approximately 150 million trades were executed during this period by a total of 354,817 traders. Regarding the different trade types, approximately 19.1% are autonomous, 4.2% are leading, 71.7% are delegation, and 5.0% are advice trades. Traders engaged in trading activity through 312 instruments. Among the instruments traded most heavily are foreign exchange rates, representing approx. 85% of all transactions, several stock market indices (approx. 7% of all transactions), and some single-name stocks (approx. 1% of all transactions). Furthermore, investors engage in commodities and digital currency trading. Finally, it is noteworthy that the data are heavily skewed towards delegation trades; but even the smallest group contains more than 6.2 million trades, which allows a rigorous statistical analysis and a comparison across trade groups.

[7] While anyone can become a leader trader, not everyone can become a copy trader. According to eToro's Terms and Conditions [1.1.3.3, p. 3], a trader can use eToro's Copytrading Services based on his or her investment profile and eToro's ongoing suitability assessments in accordance with its policies and procedures. See eToro's Terms and Conditions. https://uapi-front.etoro.com/api/v1/tnc/regulations/2.

Table 1 reports basic demographic information of the investors. Notably, the dataset contains significantly more male than female traders and most traders are relatively young (25–34 years old).

2.2. Variables

Our analysis builds on individual daily trade data and on monthly aggregated trade data. Specifically, for each trader who engages in social trading for at least five months, we aggregate the individual trade data on a monthly basis by using averages. In this way, we calculate the average number of trades per month—separated by trade type, the average holding period (in hours), the average investment as a fraction of total assets deposited with the broker, the average leverage used, count of the number of instruments used in a given month, count of the number of other investors a given trader follows in a month, i.e., takes advice from (number of followed traders), and count of the number of followers that follow a given investor, i.e., a given trader gives advice to (Number of followers). 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-month and the standard deviation of the ROI for each trader-month.

To quantify the extent to which 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 all trades that are out-of-the money exhibits the maximum disposition effect of one. Conversely, an investor who only keeps positions that are in-the-money exhibits the minimum disposition effect of minus one. If the trader equally closes profitable and non-profitable positions, her disposition effect is zero.

In addition to trading covariates, we generate two dummy variables based on demographic variables. To be specific, we generate a dummy variable *Male* that takes the value one if the investor is male, zero otherwise, and a dummy variable *Young* that takes the value one if the investor is 34 years or younger, zero otherwise.

Summary statistics of our daily trade data are presented in Table 2. The statistics indicate that, while on average trades yield a negative return, the vast majority of trades yield positive returns. `Winning trade` is a dummy variable that takes value one if a trade is closed at a profit, zero otherwise. The holding period (in hours) is skewed, with many short records. We observe that investors use significant amounts of `Leverage`, on average, which may be explained by the high fraction of trades taking place in foreign exchange. `Investment` is measured as a fraction of total assets deposited with the online broker and indicates that investors only invest small fractions of their assets per trade, on average. `Long` is a dummy variable that takes value one if a trade is a long position, zero otherwise. Investors engage almost equally in long and short positions.

Summary statistics for monthly aggregated trade data, covering 145,840 investors, are shown in Table 3. Note that we lose in-

Table 1
Summary statistics of demographic information. The table reports an overview of the gender and age distribution of investors in our data. In total, our sample contains trading data from 354,817 investors.

	Gender			Age						
	Female	Male	Missing	18–24	25–34	35–44	45–54	55–64	> 65	Missing
Total	51,316	213,376	90,125	20,476	112,906	71,681	31,666	14,085	10,011	93,992

Table 2
Summary statistics of the trade data. The table shows summary statistics of the trade data. `Winning trade` is a dummy variable taking value one if a trade is closed at a profit, zero otherwise; `ROI` denotes the return on investment; `Holding period` measures the timespan between opening and closing of a position in hours; `Leverage` denotes the leverage employed for a trade; `Investment` is measured as a fraction of total assets deposited with the online broker; `Long` is a dummy variable taking value one if a trade is a long position, zero otherwise; `Autonomous trade` is a dummy variable taking value one if a trade is an autonomous trade, zero otherwise; `Leader trade` is a dummy variable taking value one if a trade is duplicated by other investors, zero otherwise; `Delegation trade` is a dummy variable taking value one if a trade is a result of an automatic duplication strategy employed by an investor, zero otherwise; `Advice trade` is a dummy variable taking value one if a trade is a result of a manual duplication strategy of an investor, zero otherwise; `Number of followers` denotes the number of other trades that are executed as a result of a duplication strategy of this trade. We report `Number of followers` twice, once only for trades that are duplicated at least once, and once for all trades. In total, our sample runs from January 1, 2012, to October 8, 2015, and contains approx. 150 million trades from 354,817 investors.

	Obs	Mean	SD	P25	P50	P75
Winning trade	149,250,254	0.794	0.404	1	1	1
ROI	149,250,254	−0.0001	0.005	0.00005	0.0004	0.001
Holding period	149,250,254	112.052	603.525	0.926	5.034	31.853
Leverage	149,250,254	101.714	110.547	25	50	100
Investment	149,250,254	4.468	11.312	0.170	0.540	2.380
Long	149,250,254	0.545	0.498	0	1	1
Autonomous trade	149,250,254	0.191	0.393	0	0	0
Leader trade	149,250,254	0.042	0.200	0	0	0
Delegation trade	149,250,254	0.717	0.451	0	1	1
Advice trade	149,250,254	0.050	0.218	0	0	0
Number of followers (leader only)	6,254,469	18.845	162.907	1	1	3
Number of followers (all trades)	149,250,254	0.790	33.562	0	0	0

Table 3
Summary statistics of monthly aggregated trade data. The table shows summary statistics of the monthly aggregated trade data variables. `Disposition effect` is estimated as the difference between the proportion of realized gains and the proportion of realized losses,where 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*) at the end of each trading day; `Avg. ROI` denotes the average return on investment per trader-month; `SD ROI` denotes the standard deviation of the ROI for each trader-month; `No. autonomous trades` denotes the number of autonomous trades executed by an investor per month; `No. advice trades` denotes the number of manually duplicated trades executed by an investor per month; `No. delegation trades` denotes the number of automatically duplicated trades executed by an investor per month; `Avg. holding period` measures the average timespan between opening and closing of a position in hours; `Avg. investment` denotes the average fraction of total assets deposited with the online broker invested in a single trade; `Diversification` is a dummy variable that takes the value one if a trader does not invest more than 20% of her wealth in a single trade, zero otherwise; `Avg. leverage` denotes the average leverage employed for a trade; `No. instruments` denotes the number of different instruments that an investor trades in a given month; `Number of followed traders` denotes the number of other traders of whom the investor duplicates (manually or automatically) trades from in a given month; `Number of followers` denotes the number of other traders that duplicate (manually or automatically) trades from the investor in a given month. Aggregated data only considers investors who trade at least five month on the trading platform. In total, monthly data contains trading information from 145,840 investors.

Variable	Obs	Mean	SD	P25	P50	P75
Disposition effect	1,584,280	0.359	0.333	0.089	0.382	0.618
Avg. ROI	1,584,273	−0.001	0.003	−0.001	−0.00001	0.001
SD ROI	1,495,403	0.006	0.006	0.002	0.004	0.007
No. autonomous trades	1,584,280	13.953	33.150	0	0	10
No. advice trades	1,584,280	3.431	18.994	0	0	1
No. delegation trades	1,584,280	61.169	173.271	0	10	51
Avg. holding period	1,584,280	234.095	504.520	25.826	73.880	200.367
Avg. investment	1,584,280	11.940	19.657	0.978	3.200	13.208
Diversification	1,584,280	0.666	0.472	0	1	1
Avg. leverage	1,584,280	92.264	88.060	36.500	67.887	100.000
No. instruments	1,584,280	6.458	5.903	2	5	9
No. followed traders	1,584,280	1.872	2.490	0	1	2
No. followers	1,584,280	2.207	72.394	0	0	0

Table 4
Summary statistics of leader trade data (monthly). The table shows summary statistics of the monthly aggregated trade data variables for leader traders only. Variable definitions are the same as in Table 3. Aggregated data only considers investors who trade at least five month on the trading platform. In total, monthly leader data contains trading information from 29,297 leaders.

Variable	Obs	Mean	SD	P25	P50	P75
Disposition effect	113,889	0.435	0.304	0.216	0.495	0.670
Avg. ROI	113,889	−0.0004	0.003	−0.001	−0.00003	0.001
Avg. ROI (lagged)	103,715	−0.001	0.005	−0.001	0.0001	0.001
SD ROI	111,748	0.007	0.007	0.002	0.005	0.008
No. individual trades	113,889	36.257	53.150	0	11	49
No. advice trades	113,889	6.585	33.765	0	0	1
No. delegation trades	113,889	93.118	267.877	0	1	67
Avg. holding period	113,889	170.366	352.376	27.540	68.671	161.687
Avg. investment	113,889	7.945	13.121	0.817	2.633	9.030
Diversification	113,889	0.658	0.474	0	1	1
Avg. leverage	113,889	105.825	88.434	50.000	85.946	123.091
No. instruments	113,889	8.503	6.968	3	7	12
No. followed traders	113,889	2.659	3.567	0	1	4
No. followers	113,889	30.704	268.385	1	1	4

Table 5
The disposition effect across gender and age. The table reports the disposition effect from Table 3 separately for male and female investors and across different age ranges.

	Gender		Age					
	Female	Male	18–24	25–34	35–44	45–54	55–64	>65
Mean	0.4030	0.3398	0.2950	0.3367	0.3547	0.3673	0.3778	0.3828
SD	0.3242	0.3327	0.3430	0.3367	0.3291	0.3257	0.3231	0.3281

vestors as a result of our requirement that investors trade at least five months on the social trading platform to be included in the monthly aggregated dataset. This is in line with previous findings in the literature suggesting that a large number of investors only briefly engage in social trading (see, e.g., Pelster, 2017). In total, our dataset contains 1,584,280 investor-months observations. Summary statistics for leader trade data at the monthly level is reported in Table 4. Our dataset contains 113,889 investor-months of leader traders. In total, the monthly aggregated data set contains 29,297 leaders.

Interestingly, we observe that leader traders are on average more susceptible to the disposition effect. Moreover, they execute significantly more trades than other traders. Leader traders also show a significantly shorter holding period and tend to use more leverage. Regarding their performance, we observe a slightly larger performance for leaders, albeit still negative, on average. We also observe a slightly negative past performance for leader traders.

Finally, Table 5 presents the distribution of the average disposition effect across gender and age ranges. Interestingly, the disposition effect is more pronounced for female investors which is in line with previous experimental results (e.g., Rau, 2014). Similarly, we observe that the disposition effect increases with age.

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 Fig. 1 displays the fractions of winning trades ($N_+/N_+ + N_-$) for the different trader types. The data shows significantly more winning than losing trades, and 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. This 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 prefer a specific segment of leader traders. Hence, this part of the leader group is assigned a greater weight (since they have more followers). Our results underline 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 to select the "right" investors to follow (i.e., followers seem to be able to identify specifically those investors who have a high ratio of winning trades).

When considering the ROI, the situation is quite different, as can be seen in Panel (b) of Fig. 1). On average, ROI is negative except for the delegation group that exhibits significantly higher ROIs. In general, substantial differences across groups result. The graphical illustration is confirmed by a simple t-test ($p < .01$). Thus, although the fraction of profitable trades is higher than that of non-profitable trades, this does not necessarily lead to positive ROIs for most groups. To explain this, we separately study the ROIs of profitable (Fig. 1, Panel (c)) and unprofitable positions (Fig. 1, Panel (d)). Here, we again find significant group differences. For example, profitable advice trades exhibit the highest ROI; 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, delegation trades significantly outperform ($p < .01$) autonomous, leader, and advice trades. Despite leader trades showing, on average, negative ROIs, delegation trades realize, on average, positive ROIs. This again indicates that most followers seem to be able to select the "right" investors to follow. Moreover, the high fractions of winning trades might be a first indicator that these investors are subject to the disposition effect.

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 ($t = t_{closed} - t_{opened}$). Holding time distributions for positive and negative trades are calculated separately, based on their ROI. Positions exactly breaking

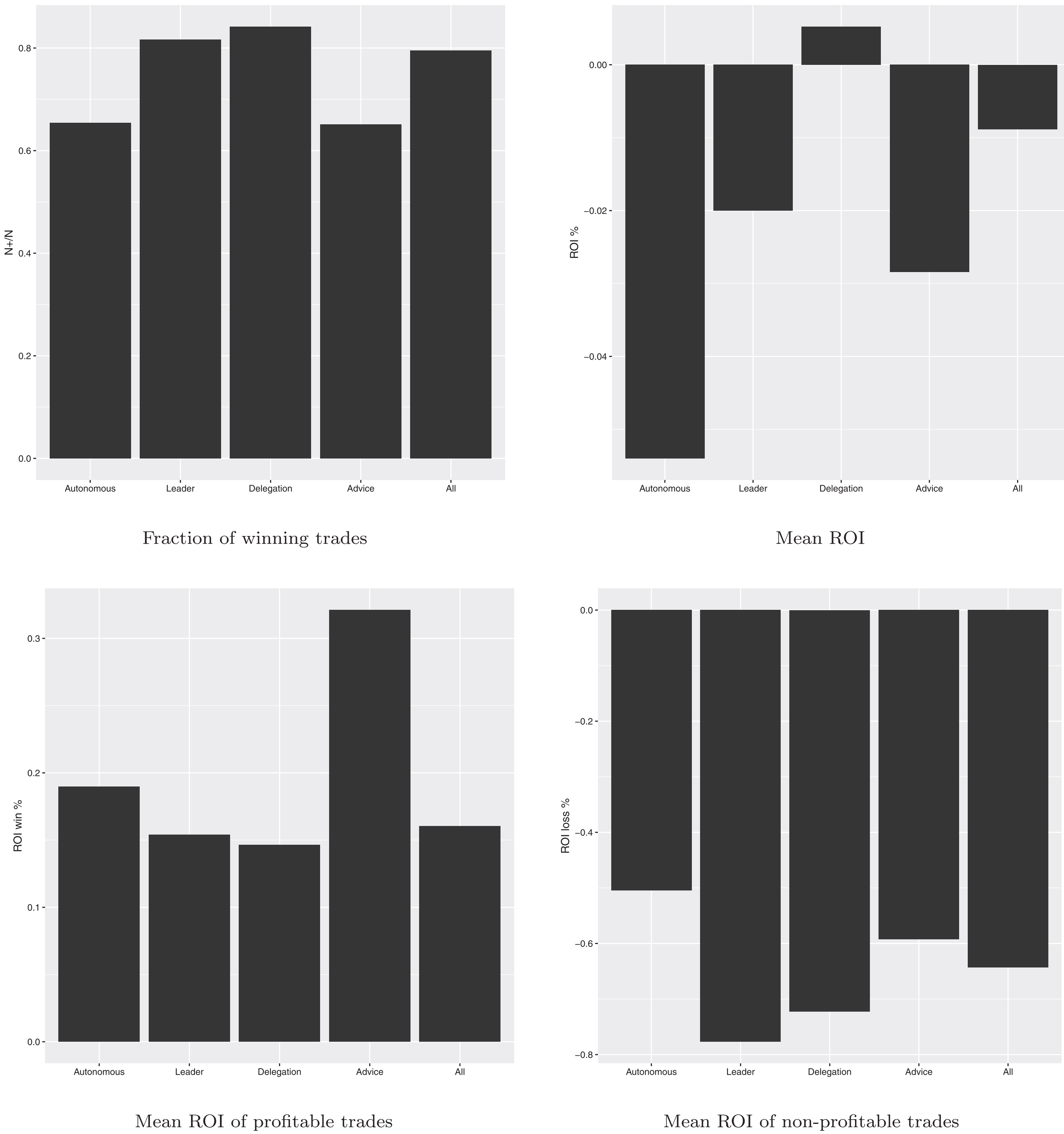
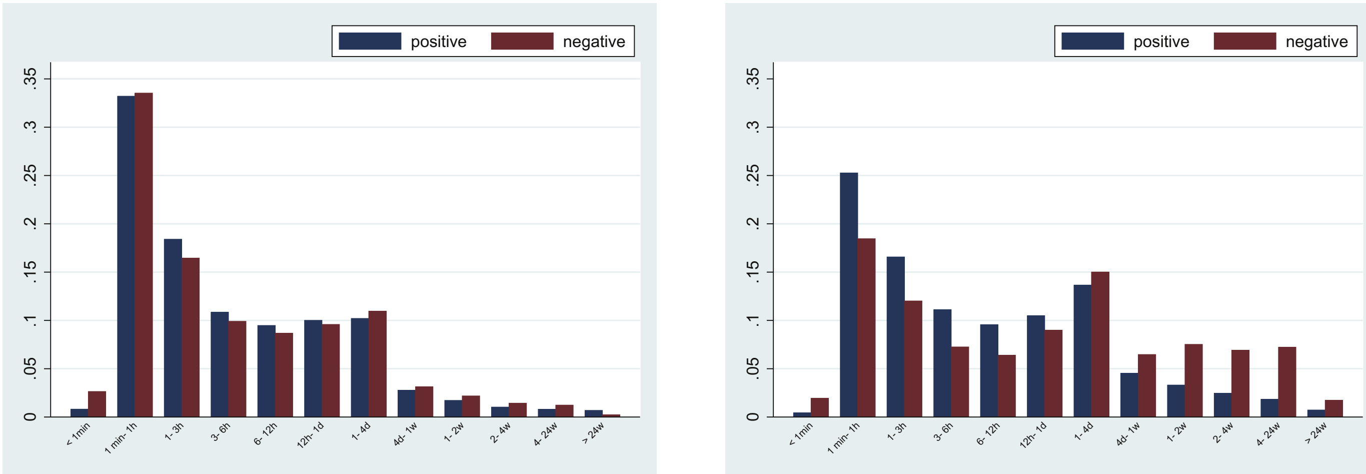


Fig. 1. Performance comparison of social and non-social trade types. The figure presents a comparison of the performance of different investors on a social trading platform. Panel (a) displays the fraction of profitable trades; Panel (b) displays the average ROI by trade type. The bottom figures show the average ROI for different trade types for profitable (Panel (c)) and non-profitable trades (Panel (d)).

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 Fig. 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 ($p < .01$). On average, positive trades are held for a shorter time period than negative trades (except for holding times of less than one minute).

From autonomous to leader 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 pe-



Autonomous trades

Leader trades

Fig. 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 by trade groups. The left panel (a) shows the distribution for autonomous trades and the right panel (b) shows leader trades.

Table 6
Hazard estimates of autonomous and leader trades. The table shows estimates of the determinants of the hazard rate to closing a position using a Cox proportional hazard model. Profitable trade is an indicator variable that equals one if a position is profitable, zero otherwise. Model (1) is restricted to autonomous trades; Model (2) is restricted to leader trades. Estimates are based on daily trade data. Standard errors are in parentheses.

	(1)		(2)	
	Autonomous trades		Leader trades	
	coef	odds ratio	coef	odds ratio
Profitable trade	0.0456	1.05	0.461	1.586
	(0.00)		(0.00)	
Number of trades	28,876,172		6,254,469	

riods. 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 his or her favor.

3.1.2. The disposition effect

We visualize the disposition effect by plotting the estimates of Kaplan–Meier survival functions, separately for autonomous trades and for leader trades. The Kaplan–Meier survival functions represent the cumulative densities of open trades as a function of holding time. Survival functions 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. The disposition effect is revealed 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. Fig. 3 indicates that both autonomous and leader traders are subject to the disposition effect. Most interestingly, the disposition effect—as illustrated by the Kaplan–Meier survival functions—is more pronounced for leader traders. Hazard rate estimates from a Cox proportional hazard model, which are reported in Table 6, confirm the Kaplan–Meier estimates. Thus, this first preliminary evidence suggests that leader traders differ substantially in their trading behavior as compared to autonomous traders.

To offer some preliminary insights into the effect of the number of followers on the disposition effect, we provide summary statistics of the disposition effect with respect to the number of followers in Table 7. Using monthly aggregated data, we group investors into six distinct groups depending on the number of other investors following their trading strategy. We observe a disposition effect of 0.3536 for investors who are not being followed by others. The disposition effect increases monotonically in the number of followers. For example, for investors with 100 or more followers, we observe a disposition effect of 0.4989. This indicates that the size of the audience that follows one's investment decisions is related to one's disposition effect. Regardless of the number of followers, female investors are always more susceptible to the disposition effect than male investors.

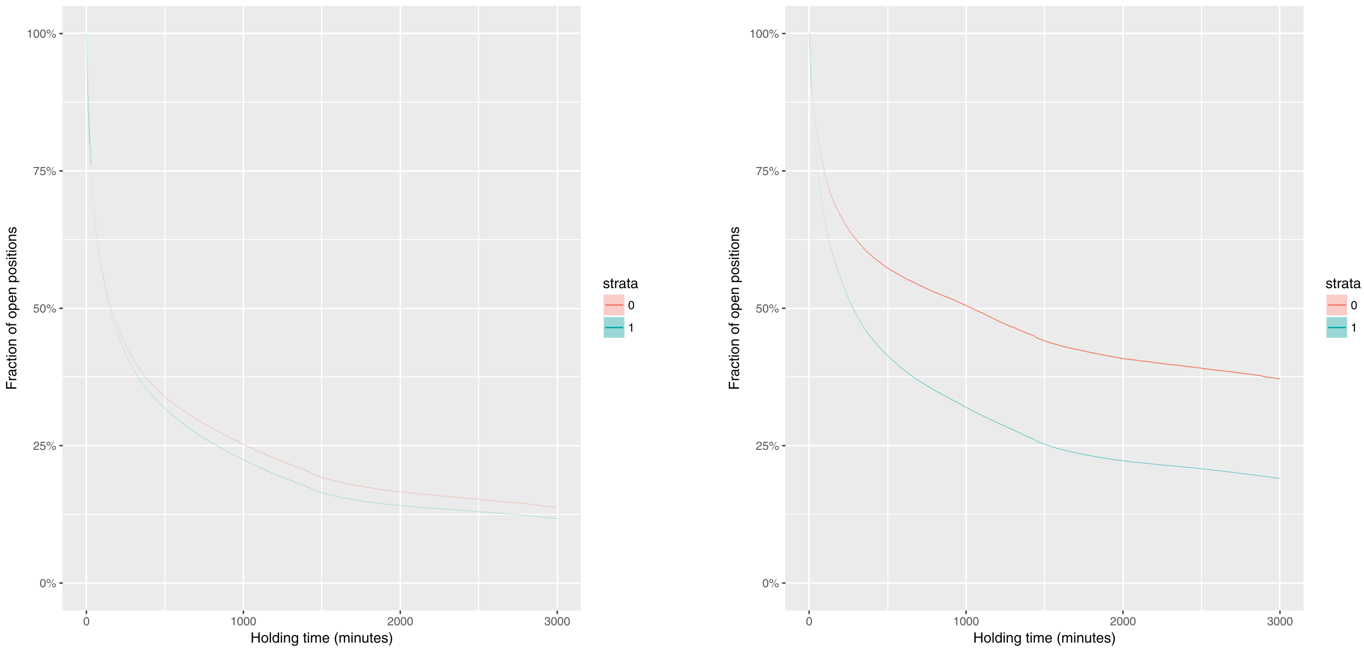
3.2. Determinants of the probability of closing existing positions

What are the determinants of the probability of traders closing existing positions? As suggested by the descriptive data above, we predict that (i) winning positions are significantly more likely to be closed, and (ii) the probability of closing winning positions differs significantly between autonomous and leader traders.

We use a probit model to predict the probability of closing positions. We include all positions of autonomous and leader traders that were opened and closed on different trading days in this analysis, using multiple observations per trade. We include one observation for every 24-h holding period until the position is closed. 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`. This 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. More formally, we estimate the following model:

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

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 divide our explanatory variable into two distinct variables, one for autonomous and one for leader trades. For example, the variable `Profitable trade, autonomous trade` takes value one if the position currently exhibits positive paper profits and is an autonomous trade, zero



Autonomous trades Leader trades

Fig. 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 one if a position is closed, zero 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. The figure is based on daily trade data. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Table 7
Disposition effect by number of followers. The table shows mean and standard deviation of the disposition effect from Table 3 with respect to the number of followers for the entire dataset and separately for female and male investors. *n* denotes the number of investor-month.

Follower	All investors			Female investors			Male investors		
	Mean	SD	n	Mean	SD	n	Mean	SD	n
0	0.3536	0.3346	1,470,391	0.3975	0.3261	247,407	0.3327	0.3338	1,083,484
1	0.4171	0.3052	61,141	0.4538	0.2962	11,565	0.4063	0.3060	47,618
2-4	0.4455	0.3029	27,299	0.4723	0.2921	4951	0.4371	0.3046	21,494
5-7	0.4514	0.3017	6547	0.5084	0.2795	1157	0.4376	0.3054	5193
8-99	0.4648	0.3008	14,552	0.4965	0.2841	2646	0.4555	0.3045	11,606
> 99	0.4989	0.2881	4350	0.5000	0.2783	658	0.4987	0.2900	3673

otherwise. We use these separate variables to study differences across trade groups. As control variables, we include a dummy variable for leader trades (autonomous trades are the baseline) and a dummy variable that captures whether the position is long or short (Long). We include month dummies to control for aggregate time-trends.

Table 8 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 the 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 here.

We observe that profitable trades are more likely to be closed. This result holds equally for autonomous and leader trades and is consistent with the disposition effect. For autonomous trades, the probability that the position is closed on a given trading day increases by 7.0% if the position is currently profitable. This result is even more pronounced for leader trades (15.1%). In Model 2, 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. This variable confirms our previous findings. In summary, the empirical evidence in this section suggests that leader traders are more susceptible to the disposition effect than investors who are not being followed.

3.3. Do newly appointed leaders change their trading behavior?

The descriptive data and the probit analyses above suggest that leader traders exhibit a significantly larger disposition effect than traders who are not being followed by others. We hypothesize that investors with followers become more susceptible to the bias. 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 realized performance but can also deter (potential) followers. In the following, we thus test whether investors' propensity for the disposition effect increases when they are followed by other traders for the first time. To identify whether leaders change their

Table 8
Probability that investors will close an existing position (marginal effects). The table reports the marginal effects of our probit regressions. The model includes multiple observations per each trade, one for every 24-h holding period until the position is closed. The dependent variable is a dummy variable taking value one if the open position is closed on a given day, zero otherwise. `Profitable trade, autonomous trade` is a dummy variable that takes value one if the position currently exhibits positive paper gain and is an autonomous trade, zero otherwise; `Profitable trade, leader trade` is a dummy variable that takes value one if the position currently exhibits positive paper gain and is a leader trade, zero otherwise; `Profit, autonomous trade` denotes the current paper gains and losses of autonomous trades and is zero for leader trades; `Profit, leader trade` denotes the current paper gains and losses of leader trades and is zero for autonomous trades; `Long` is a dummy variable taking value one if a trade is a long position, zero otherwise; `Leader trade` is a dummy variable taking value one if a trade is duplicated by other investors, zero otherwise. Standard errors are clustered at the individual investor level to mitigate possible issues due to heteroscedasticity and serial correlation. Standard errors are in parentheses. As standard errors in the multivariate regression framework decrease in the 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. The table is based on all positions of autonomous and leader traders that were opened and closed on different trading days.

	(1)	(2)
Profitable trade, autonomous trade	0.070	
	(0.001)	
Profitable trade, leader trade	0.151	
	(0.003)	
Profit, autonomous trade		0.026
		(0.004)
Profit, leader trade		0.355
		(0.029)
Long	−0.048	−0.039
	(0.001)	(0.001)
Leader trade	−0.082	−0.056
	(0.002)	(0.002)
Observations	231,891,774	231,891,774
Trader	231,708	231,708
Chi^2	39,572.0	19,036.0
Pseudo R^2	0.10	0.05

Table 9
The disposition effect of new leader traders. The table reports the results of our difference-in-differences estimations of the disposition effect of investors on the social trading platform of the month that they are followed by another trader for the first time. `Post treatment` is a dummy variable that takes a value of one after investors become leaders for the first time, zero otherwise; `Treatment group` is a dummy variable that takes a value of one for investors of the treatment group, zero otherwise; `Treatment` denotes the interaction of `post treatment` and `treatment group`; `Male` is a dummy variable that takes a value of one for female investors, zero otherwise; `Young` is a dummy variable that takes a value of one for investors who are 34 years or younger, zero otherwise. Controls include variables that capture investors' trading activity (their monthly number of trades, average leverage, average holding period, the diversification dummy, number of instruments, the number of followed traders), and investors' performance (average ROI). Variable definitions on investors' trading activity can be found in Table 3. Non-treated investors are matched based on demographic covariates and covariates characterizing the past trading behavior. *t*-statistics are reported in parentheses.

	(1)	(2)	(3)
Post treatment × treatment group	0.05	0.05	0.05
	(24.63)	(14.57)	(21.17)
Treatment × Male		−0.00	
		(−0.41)	
Treatment × Young			0.00
			(1.28)
Controls	Yes	Yes	Yes
Investor fixed effects	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes
R^2	0.07	0.07	0.07
Obs.	78,324	78,324	78,324

behavior after becoming leaders, a difference-in-differences approach is used.

The treatment group consists of investors who are followed by another trader for the first time. The initial dataset contains 29,297 investors who, at some point over our sample period, are followed by another trader. Note, however, that several of these investors already have had followers before our sample period begins or already have followers in the first months of our sample period. Therefore, we have to exclude these investors from the difference-in-differences analysis. As a result, our treatment group consists of 19,591 investors eligible for the difference-in-differences analysis. We compare the disposition effect of newly appointed leaders before and after treatment (which is the event of being followed for the first time) with that of a control group. We do not include all other investors in this control group; rather, we employ a nearest-neighbor-matching approach to find traders with similar trading strategies. In more detail, control traders are matched based on the following covariates from the last month before the treatment event of the treated investor: gender, age range, disposition effect, average number of trades per month, average holding period, average investment, the number of different instruments traded, average leverage, the number of other traders that an investor duplicates trading strategies from, and the average ROI. These restrictions ensure that the control traders are relatively similar to the treated traders before treatment.[8] In total, we find matches for 19,581 investors in the treatment group. The after-matching comparison of the characteristics of treated and non-treated investors shows that the two groups do not differ significantly in their features prior to the treated investor being followed for the first time.

Our baseline difference-in-differences estimation is as follows:

$$\texttt{Disposition effect}_{it} = \beta_1 \cdot \texttt{Post treatment}_{it} + \beta_2 \cdot \texttt{Treatment group}_i + \beta_3 \cdot \texttt{Post treatment}_{it} \cdot \texttt{Treatment group}_i + \texttt{Controls}_{it} + \epsilon_{it}, \quad (2)$$

where `Post treatment` is a dummy variable that equals one after the treatment, regardless of whether investor i is in the treatment or control group, and zero otherwise. The variable captures all effects that are relevant for both types of investors after the treatment. `Treatment group` is a dummy variable equal to one for investors in the treatment group. It controls for all time-invariant differences between the two types of investors that are not accounted for by the matching routine. The interaction term between `Post treatment` and `Treatment group` is the central term as its coefficient captures the additional disposition effect of treated investors that is related to being followed for the first time. When estimating Eq. (2), we specify that the error term, ϵ, contains a fixed effect for each investor, which is perfectly collinear with the dummy variable `Treatment group`. We also include time fixed effects to control for aggregate time-trends. The time effects are perfectly collinear with `Post treatment`. We restrict our analysis to the immediate trading activity of investors around the treatment date to mitigate other time-varying influences on investors' trading activity.

In our baseline difference-in-differences estimation, we control for investors' trading activity with their monthly number of trades, average leverage, average holding period, the diversification dummy, number of instruments, the number of followed traders, and investors' performance with their average ROI. Table 9 presents the results. The coefficient on the treatment is positive and significantly different from zero, both statistically and economically (Model 1). This suggests that investors are indeed more susceptible to the disposition effect when they are first followed by other

[8] Investors with missing demographic information are excluded from the analysis. Treated investors for whom we do not find a control trader are also not considered in the analysis.

investors. After being followed for the first time, investors become less likely to close losing positions; their disposition effect increases. Since our descriptive analysis suggests that male and young investors may be less susceptible to the disposition effect, we additionally study how these investor types are affected when they become first-time leaders. Results suggest that neither male nor young investors seem to be particularly affected when being first followed (Model 2 and Model 3).

In summary, our results support the hypothesis that investors become more susceptible to the disposition effect when they are being followed by other investors for the first time.

3.4. The disposition effect of leader traders

In this section, we are interested in the role that followers may play when leader traders decide to close positions. We hypothesize that leaders are more concerned about closing a losing position when they have a large number of followers. For example, leader traders may be especially reluctant to close losing positions when they have a large audience (i.e., a large number of followers), given that the realization of negative profits signals a poor investment decision to (potential) followers. By maintaining a losing position, the leader does not admit having made an incorrect investment decision. Admitting a mistake is especially painful when a large group of investors follows one's trading strategy. If investors were indeed concerned about their reputation when being closely observed by others, we would expect this concern to increase in their number of followers. Leaders with many followers may be even more likely to hold losing positions open for longer, still hoping for positive returns. In other words, leader traders may be more susceptible to the disposition effect with an increasing audience. Our descriptive analysis supports this notion and suggests that investors with more followers are more susceptible to the disposition effect. In this section, we shed additional light on the relationship between the number of followers and the disposition effect in a multivariate framework.

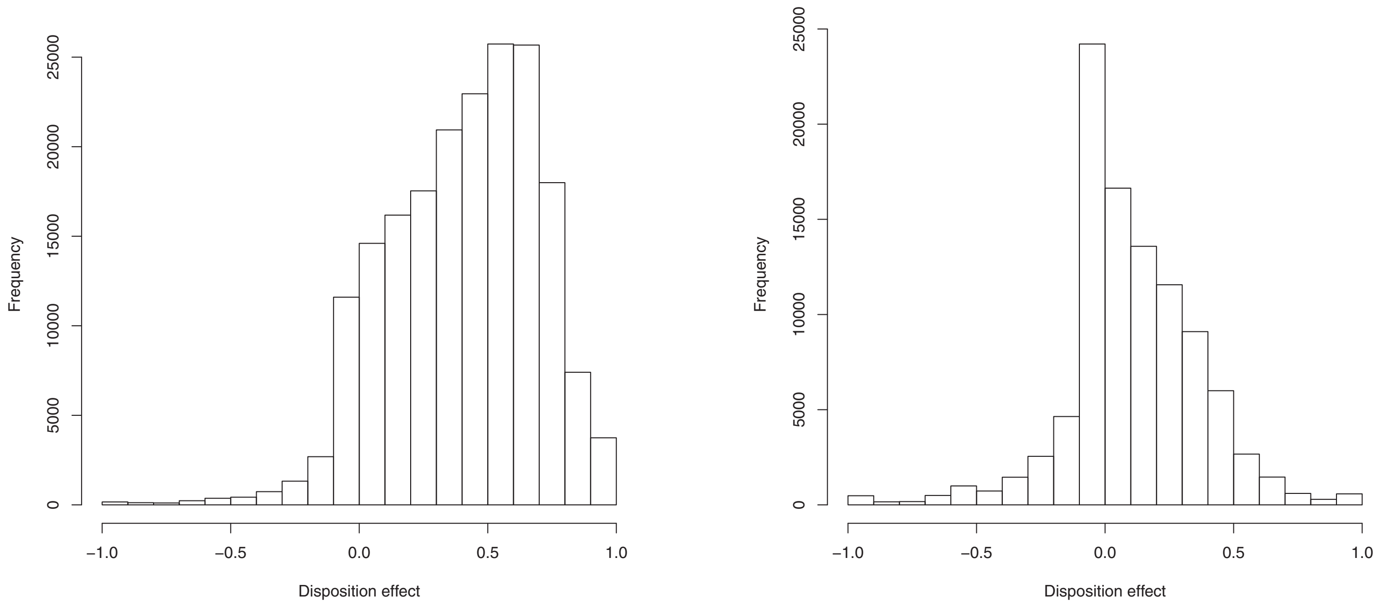
The analysis is based on those traders who are leaders at some point over our sample period.[9] We use log(1+`No. follower`) to quantify the size of the audience of investors to consider that one additional follower likely has a larger impact on the behavior of an investor when the additional follower is the third or tenth follower rather than when the additional follower is the 105th follower or 500th follower. We perform a fixed-effects panel regression analysis. In other words, we exploit the within-variation in our monthly leader data to further expose the effect of having followers on an investor's disposition effect while controlling for other trading characteristics. In addition, we include month-fixed effects to control for aggregate time-trends. Results of the fixed-effects panel regression analysis are reported in Table 10.

Model (1) only considers the correlation between the number of followers and the disposition effect. We observe a significantly positive coefficient on `Follower`. This is in line with our expectations and the results of the summary statistics reported in Table 7. The disposition effect increases in the number of followers that duplicate an investor's trading strategies. Model (2) also controls for the fraction of winning trades the investor realized in the previous month. We still observe a statistically significant correlation between `Follower` and the disposition effect. Moreover, we also find a positive correlation between the fraction of winning trades and the disposition effect. Next, Model (3) includes additional trading and performance characteristics of the investor. While the coefficient on `Follower` slightly decreases in size from Model (1) to Model (3), we nonetheless observe a significantly positive correlation between the number of followers and the disposition effect. Finally, in Model (4) we include a series of dummy variables to estimate the impact of followers on the disposition effect of leader traders. Specifically, we include a dummy variable for each of the different categories used in Table 7, where the category with zero followers is our baseline. Thus, we include a dummy variable `Follower1` that takes a value of one if the investor has one follower, zero otherwise; a dummy variable `Follower2-4` that takes a value of one if the investor has two to four followers, zero otherwise; etc. Similar to Table 7, our regression analysis indicates that the disposition effect significantly increases with the audience of an investor. This provides further evidence in support of our hypothesis that leader traders' decisions are influenced by a large audience. The disposition effect significantly increases in the number of followers.

Table 10
Panel regressions: Disposition effect for leader traders. The table shows results of the fixed effects panel regressions on leader traders' disposition effect. The regressions are restricted to investors who are leaders at some point over our sample period. The dependent variable is the disposition effect of an investor. Variable definitions on investors' trading activity can be found in Table 3. `Follower1` denotes a dummy variable that takes a value of one if the investor has one follower, zero otherwise; `Follower2-4` denotes a dummy variable that takes a value of one if the investor has two to four followers, zero otherwise; `Follower5-7` denotes a dummy variable that takes a value of one if the investor has five to seven followers, zero otherwise; `Follower8-99` denotes a dummy variable that takes a value of one if the investor has eight to 99 followers, zero otherwise; `Follower100` denotes a dummy variable that takes a value of one if the investor has at least 100 followers, zero otherwise; Standard errors control for heteroscedasticity. *t*-statistics are reported in parentheses.

	(1)	(2)	(3)	(4)
log(1 + No. follower)	0.03	0.03	0.02	
	(40.28)	(41.35)	(20.45)	
L.Frac. winning trades		0.14	0.21	0.21
		(66.68)	(73.40)	(73.39)
L.Avg. ROI			−6.66	−6.66
			(−52.05)	(−52.05)
L.SD ROI			−0.32	−0.32
			(−5.65)	(−5.65)
No. autonomous trades			0.00	0.00
			(3.02)	(2.95)
Avg. holding			−0.01	−0.01
			(−15.65)	(−15.66)
Avg. investment			−0.00	−0.00
			(−65.16)	(−65.14)
Diversification			0.04	0.04
			(33.07)	(33.02)
Avg. leverage			−0.00	−0.00
			(−13.84)	(−13.84)
No. instruments			0.00	0.00
			(21.17)	(21.16)
No. followed traders			0.01	0.01
			(60.56)	(60.48)
Follower1				0.01
				(10.06)
Follower2–4				0.02
				(12.55)
Follower5–7				0.03
				(8.18)
Follower8–99				0.04
				(14.94)
Follower100				0.05
				(11.04)
Fixed effects	Yes	Yes	Yes	Yes
Observations	378,682	378,682	378,682	378,682
Leaders	29,184	29,184	29,184	29,184
R^2	0.01	0.02	0.10	0.10

[9] Note that our analysis contains more investor-month observations than reported in Table 4 since we include the entire trading history of investors who are leaders at some point during our sample period here and do not restrict the analysis to months in which these investors are actually being followed by other investors.



Delegation traders, all trades

Delegation traders, self-executed trades

Fig. 4. The disposition effect of delegation traders. The figure shows the distribution of the disposition effect of delegation traders. The left panel (a) shows the distribution for all trades that delegation traders executed over our sample period. That is, the distribution includes trades based on their own trading behavior and trades based on the delegation of investment decisions to a leader trader; the right panel (b) includes only trades that reflect delegation traders own trading behavior.

3.5. Does a large disposition effect make traders attractive?

Our results above suggest that leader traders are more susceptible to the disposition effect than are autonomous traders which is in line with our hypothesis that investors who become leaders also become more susceptible to the disposition effect. However, our results may also be driven by a selection bias. In particular, leaders could be investors most prone to the disposition effect. They may rarely sell capital losses and mainly sell capital gains as a result of their individual investor characteristics. These trading characteristics may attract myopic delegation traders. Thus, being susceptible to the disposition effect may be an attractive feature that increases the likelihood of an investor being followed by others.

We address this issue here by studying the trading behavior of delegation and advice traders. Delegation traders delegate some part of their investment strategies to leaders. Advice traders manually copy investment strategies of leaders. However, (most) delegation and advice traders also execute some trades on their own. If these trader types indeed favor disposition-effect-related trading strategies, this should also be reflected in their own behavior, i.e., in the investment strategies which are not a result of duplication strategies.

First, we estimate the disposition effect of all trades that are executed by delegation and advice traders. The distribution of the disposition effect of these traders is shown in Panel (a) of Fig. 4. The mean disposition effect of all trades that are executed by delegation and advice traders is 0.439. Then, we estimate the disposition effect of delegation and advice traders' own trading strategies. To be specific, we only use data on individual trades of delegation and advice traders that are not duplicating any trades of others. For these trades, neither reputational concerns nor responsibility are an issue, and we should observe significantly lower susceptibility to the disposition effect. The distribution of the disposition effect of these trades is shown in Panel (b) of Fig. 4. The mean disposition effect of delegation and advice traders' own trading behavior is 0.1. This is significantly lower than the disposition effect of all trades of delegation and advice traders. We use a Kolmogorov–Smirnov test to compare the two samples and reject the null hypothesis that the samples are drawn from the same distribution (test statistic: D = 0.474, p-value = .000). These results thus support the notion that delegation and advice traders are not attracted by disposition-effect trading strategies.

The fact that delegation and advice traders display a very small disposition effect may be explained as follows: Investors who come to the platform to rely on the advice of other traders may have different motivations from investors who come to the platform to trade on their own or to become leaders. Therefore, these traders may actually be the least concerned with their reputation which explains their low susceptibility towards the disposition effect.

As a second approach to test for a potential selection bias, we study how followers select leader traders to follow. Pelster (2017) and Röder and Walter (2017) document that in social trading portfolios, the likelihood of adopting the strategy of another investor is momentum-driven and increases the other investor's past returns. Moreover, Pelster (2017) shows that the likelihood of increasing one's audience is significantly correlated with one's past return variance. This is consistent with social transmission bias (see Han et al., 2017). If our results were driven by a selection bias, the probability of increasing one's audience would also be explained by the disposition effect.

To study the selection of leader traders, we additionally estimate probit regression models using our monthly aggregated data. First, we estimate models using a dummy variable that takes value one if the investor is first targeted as an investment advisor (becomes a leader for the first time), zero otherwise, as our dependent variable. As explanatory variables, we include an investor's disposition effect as well as variables that control for trading behavior. Explanatory variables are lagged by one period. The marginal effects of our estimations are shown in the first three columns of Table 11. While the coefficient on the disposition effect is significantly different from zero, the reported marginal effects are very small. In fact, the probability that an investor becomes a leader for the first time increases by less than one percent for a one-standard-deviation increase in his or her disposition effect.

Table 11
Probability that investors will increase their audience (marginal effects). The table reports the marginal effects of our probit regressions. In the first three columns, the dependent variable is a dummy variable taking value one if the investor becomes a leader for the first time, zero otherwise. In the final three columns, the dependent variable is a dummy variable taking value one if the investor increases her audience in a given month, zero otherwise. Variable definitions on investors' trading activity can be found in Table 3. *t*-statistics are reported in parentheses. Standard errors are double-clustered at the individual investor level and over time to mitigate possible issues due to heteroscedasticity and serial correlation.

	(1)	(2)	(3)	(4)	(5)	(6)
	First-time Leader	First-time Leader	First-time Leader	Increase Follower	Increase Follower	Increase Follower
L.Disposition effect	0.007		0.003	0.017		0.010
	(4.31)		(1.94)	(8.31)		(4.58)
L.Frac. winning trades		0.020	0.021		0.037	0.035
		(8.64)	(9.93)		(11.32)	(10.06)
L.ROI	0.284	0.187	0.222	0.424	0.346	0.377
	(3.71)	(3.12)	(3.42)	(4.43)	(3.23)	(4.21)
L.ROI^2	0.147	0.121	0.116	0.773	0.218	0.662
	(3.56)	(3.97)	(3.07)	(5.08)	(3.92)	(4.50)
L.SD ROI	0.070	0.031	0.024	0.240	0.256	0.210
	(0.97)	(0.59)	(0.44)	(3.46)	(2.22)	(3.42)
L.SD ROI^2	−0.156	−0.059	−0.056	−0.362	−0.404	−0.299
	(−1.25)	(−1.30)	(−1.00)	(−4.87)	(−1.48)	(−4.64)
L.Avg. holding period	−0.005	−0.005	−0.005	−0.005	−0.006	−0.006
	(−9.10)	(−9.64)	(−9.92)	(−5.88)	(−6.89)	(−6.88)
L.Avg. investment	0.000	0.000	0.000	0.000	0.000	0.000
	(4.53)	(.18)	(6.13)	(2.69)	(3.01)	(3.79)
L.Avg. leverage	0.000	0.000	0.000	0.000	0.000	0.000
	(3.12)	(3.67)	(3.92)	(7.00)	(7.75)	(8.16)
L.No. instruments	0.001	0.001	0.001	0.001	0.001	0.001
	(10.31)	(11.58)	(11.85)	(9.48)	(10.70)	(10.78)
Observations	1,083,601	1,120,262	1,083,601	1,083,601	1,120,262	1,083,601
Trader	173,626	179,035	173,626	173,626	179,035	173,626
Chi^2	6043.0	6366.1	6480.4	4970.8	5671.7	5621.4
Pseudo R^2	0.03	0.03	0.03	0.02	0.02	0.03

Instead, our results indicate that investors' likelihood to become a leader for the first time significantly increases in their past performance.

In the final three columns of Table 11, we estimate probit models using a dummy variable that takes value one if an investor increases his or her audience in a given month (i.e., if the change in the number of followers is positive in a given month), zero otherwise, as our dependent variable. We include the same lagged independent variables as before. Again, we observe a statistically significant coefficient on the disposition effect with a very small marginal effect. Instead, our results are in line with previous literature (Pelster, 2017) and indicate that followers select leader traders primarily based on their past performance.

We conclude that being more susceptible to the disposition effect does not meaningfully increase a trader's likelihood of gaining additional followers. This suggests that our results are not driven by a selection bias.

3.6. The disposition effect and investor experience

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). Moreover, experimental evidence by Hermann et al. (2017) suggests that especially inexperienced investors with a higher degree of social-value orientation exhibit a larger disposition effect when deciding on behalf of others. In this section, we analyze the impact of investor experience on the leader traders' disposition effect.

In order to distinguish between experienced and inexperienced traders, we first calculate an investor's experience in each month as the time difference between the current month and the month of the first-observed trading activity in our sample period. We then split the sample at the median value and create a dummy variable `Inexperience` that takes a value of one if the investor has below median experience, zero otherwise.[10] Table 12 reports mean and standard deviation of the disposition effect with respect to the number of followers, separated by investor experience. In line with the results presented by Da Costa et al. (2013) and Hermann et al. (2017), we observe a larger disposition effect for inexperienced traders across the board.

Table 12
Inexperienced leaders and the disposition effect. The table shows mean and standard deviation of the disposition effect from Table 3 with respect to the number of followers separated by investor experience. We split our sample at the median value for investor experience. `Inexperience` is a dummy variable that takes a value of one if the investor has below median experience, zero otherwise. *n* denotes the number of investor-month.

Follower	Inexperience	Mean	SD	n
0	0	0.3376	0.3426	749,487
	1	0.3703	0.3253	720,904
1	0	0.4085	0.3139	31,088
	1	0.4260	0.2957	30,053
2–4	0	0.4283	0.3116	15,786
	1	0.4692	0.2889	11,513
5–7	0	0.4371	0.3060	4102
	1	0.4754	0.2929	2445
8–99	0	0.4492	0.3034	9709
	1	0.4959	0.2930	4843
≥ 99	0	0.4896	0.2908	3338
	1	0.5295	0.2770	1012

To analyze whether investor experience also moderates the impact of an investor being followed for the first time, we repeat our difference-in-differences analysis and include `Inexperience` as

[10] In additional robustness checks, we split the sample at the bottom quartile and observe similar results.

additional control variable as well as in an interaction term. However, while Table 12 indicates that the disposition effect is larger for inexperienced investors in general, we do not find any statistically significant effect of `Inexperience` on our treatment, i.e., the event that an investor becomes a leader for the first time. The coefficient on the interaction term in our difference-in-differences analysis is not statistically different from zero. We do not tabulate these results here in order to preserve space.[11]

3.7. 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. Note, that foreign exchange trades represent a significant part of trades worldwide. As discussed in the literature, foreign exchange and equity markets are fundamentally different from one another. For example, Locke and Mann (2005) note that the trading speed and position size in equity and foreign exchange markets differ significantly. Consequently, foreign exchange investors may follow different investment patterns than stock market investors. This is supported by O'Connell and Teo (2009), who show that investors in foreign exchange markets close their positions much more quickly if they display paper losses. In a related contribution, ter Ellen et al. (2017) 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 analyses with separate subsamples, first including only those investors with a focus on foreign exchange trading and second including only investors with a focus on stock market trading. Our results suggest that—with regard to the relation between the number of followers and the disposition effect—no notable differences between foreign exchange and stock market investors exist. We do not tabulate these results here in order to preserve space.[12]

4. Conclusions

This article studies the relationship between financial advice givers and the disposition effect in a social trading environment. A large and unique dataset allows us to study the trading behavior of different trader types in such an environment. Our results suggest a significant correlation between the number of investors copying trading strategies of others and the manifestation of their disposition effect. Traders with many followers are less likely to close losing positions. We use a difference-in-differences analysis to study behavioral changes in investment decisions when investors become leaders, i.e., are being followed by others for the first time. We find that investors significantly increase their disposition effect as a response to this event. This finding holds true for investors who engage in foreign exchange trading and for traders of stocks and stock market indices. Showing further that delegation and advice traders do not seem to be particularly attracted to the disposition effect, we provide evidence that our findings are not the result of a selection bias. An interesting finding is that, regardless of the number of followers, female investors are always more susceptible to the disposition effect than male investors.

Traders' reputational concerns may influence their trading behavior. It may be that leaders feel responsible for their followers and hence feel an urge to not fail them. This behavior may be driven by fear of losing followers when publicly admitting a bad investment decision. Alternatively, it may represent an attempt by newly appointed leaders to manage their social image and/or self-image and signal confidence in their initial investment strategy. Holding negative trades signals to followers some confidence in the financial strategy, and does not adversely affect realized performance or ranking because unrealized losses are not reflected in end returns. Thus, our results suggest that the disposition effect is boosted by fear of reputational loss when leader traders are observed by their peers.

This article demonstrates that advice seekers may need to monitor newly appointed advisors closely, as advisors may change their investment behavior. The observed investment activities before the leader-follower relationship is established are no guarantee that similar investment behavior will follow in the future. Previous activities do not account for possible changes in behavioral biases after an investor is followed for the first time.

This paper further suggests that newly appointed investment advisors should attempt to uncouple from their biases. Once they have an understanding that they tend to be susceptible to a more pronounced bias, this effect could be addressed. 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. Our study highlights the importance of understanding behavioral biases when offering financial advice.

Regarding the behavioral finance literature, our study expands current research by Rau (2015), Heimer (2016), and Hermann et al. (2017) who show that investors exhibit a larger disposition effect in social environments. More precisely, while Rau (2015) shows that the disposition effect is higher in team decisions, Heimer (2016) provides empirical evidence that investors' disposition effect increases when they begin to trade open to the public. This paper shows that this tendency increases even more when investors become signal providers in a transparent trading environment and are accepted as peer-to-peer advisors. These findings are underlined by the recent experimental study of Hermann et al. (2017) who find that especially pro-social inexperienced investors display a higher disposition effect when trading on behalf of others. Such findings are, however, not undisputed. A contemporaneous study by Lukas et al. (2017) argues that the increased transparency of investors trading in a way that is visible to the public reduces the disposition effect in social trading. We offer a possible explanation to reconcile these conflicting results: Each brokerage service utilizes a unique design for its website, and the organization of information may be different across brokerage services, different information may be highlighted, or different colors may be used to highlight information. Since the way individuals react to a particular choice is different depending on how that choice is presented to them (Tversky and Kahneman, 1981), the partly contradicting evidence between the different archival studies may be explained by different methods of framing information. In particular, the framing of the trading platform may influence how exactly investors try to manage their social and self-image. As the social trading platform analyzed in this paper displays investors' fraction of winning trades rather prominently on investors' profile pages, investors may aim to increase their fraction of winning trades in order to manage their impression.

They can do so by closing winning trades early and holding on to losing trades longer—i.e., they display a large disposition effect. Only if brokerage services represented the different choices to their traders in the same way, equal decision-making should be expected. As a consequence, future research should study how the framing of social trading decisions serves as a mediator for the influence social interaction exerts on investors' trading behavior.

[11] Results can be obtained from the authors upon request.

[12] Results can be obtained from the authors upon request.

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