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# Social recognition and investor overconfidence *

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**Abstract** We investigate the trading patterns of 21,694 investors who received social recognition for their investment decisions between 2012 and 2015. We find that confirmatory social recognition leads to increased trading activity, which can be explained by overconfidence associated with biased self-attribution and misinterpretation of observed feedback. On average, investors execute 29 additional trades in the month after receiving confirmatory social recognition for the first time. We further demonstrate that under certain circumstances, the effect of social recognition on trading activity is greater than that of financial outcomes. An experimental study supports the notion that social recognition increases investor overconfidence.

**Keywords:** social interaction; overconfidence; investor behavior; trading activity; feedback

**JEL Classification:** G11, G12.

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*Investing in speculative assets is a social activity. Investors spend a substantial part of their leisure time discussing investments, reading about investments, or gossiping about others' success or failures in investing.*

(Shiller, 1984)

Empirical studies have provided abundant evidence for the influence of social interaction on peoples' investment decisions.[1] For instance, households' stock purchases are significantly influenced by neighbors' purchases of stocks and local peers' recent stock returns (Hong et al., 2004; Ivkovic and Weisbenner, 2007; Kaustia and Knüpfer, 2012). Similarly, Duflo and Saez (2002, 2003) report that people's decision-making with respect to particular retirement plans is influenced by the decisions of their colleagues, family, and friends. The trading decisions not only of households but also of professional investors are influenced by recent communication with peers (Shiller and Pound, 1989).[2] More recent findings also indicate that individuals' cognitive biases are influenced by peoples' social environment (Heimer, 2016). In particular, Heimer (2016) finds that traders' tendency to close winning trades while simultaneously holding on to losing positions is twice as pronounced when individuals are involved in social interactions. In this study, we aim to investigate whether individuals' social environment influences their tendency to overestimate their own ability, i.e. their overconfidence.

Overconfidence is among the most common and well-known psychological biases affecting individuals' decision-making and has been found to be associated with active trading and high trading activity (Daniel et al., 1998; Odean, 1999; Barber and Odean, 2000, 2001). Overconfidence has implications for overall stock market returns (see, e.g., Hirshleifer, 2001; Statman et al., 2006). Being overconfident with respect to their ability to evaluate stock-price-related information compels investors to trade more actively (Grinblatt and Keloharju, 2009) and in a more speculative manner, and as a consequence, they tend to

[1] Social interaction involves the transfer of information among investors and affects professional and retail investors' decisions-making. For empirical evidence on this topic, see, e.g., Shiller (1984, 2010a); Kelly and Gráda (2000); Massa and Simonov (2005); Brown et al. (2008); Cohen et al. (2007, 2010); Shive (2010); Georgarakos and Pasini (2011); Heimer (2014).

[2] Results confirming this finding are reported by Hong et al. (2005) and Crawford et al. (2017).

lose money (see, e.g., Barber and Odean, 2001; Choi et al., 2002). The overconfidence bias is omnipresent and complex. For instance, individuals' overconfidence is not static but varies over time. In fact, overconfidence is closely related to investors' perceived feedback in response to previous decisions and has been widely studied as a function of past returns.

In line with Heimer and Simon (2013) and Burks et al. (2013), we argue that overestimating one's own ability is not only determined by observed monetary outcomes but also by the feedback of one's peers who endorse or disapprove previous decisions. Specifically, we argue that the potential for and experience of confirmatory social feedback—social recognition—not only motivates investors to share their trading strategies (see also Han et al., 2017) but also changes their behavior in accordance with the response of their social environment. Investors gain utility from the attention and positive recognition they receive from their peers. In short, making money feels good, but telling others about it and earning others' respect feels even better. In this paper, we study the impact of feedback, particularly the impact of social recognition on investors' trading activity. We aim to answer the question of whether social recognition affects individuals' trading activity. We hypothesize that positive feedback from peers regarding an investment decision will impact investors' future trading behavior—especially in situations where market movements provide ambiguous signals about the success of a trade. Moreover, we directly investigate the causal influence of social recognition on investors' overconfidence.

For most people, interaction with the social environment is a part of everyday life. They interact with their social environment in various circumstances (e.g., at work or in sports clubs). A large portion of people's interactions with the social environment occurs in online social networks such as *Facebook*—which has become a part of most people's everyday lives.[3] Similarly, financial market participants increasingly use online brokerage services to manage their portfolios (see, e.g., Barber and Odean, 2002; Choi et al., 2002).[4]

[3]In the last quarter of 2017, *facebook.com* recorded 239 million active users in North America (USA and Canada; 2.129 billion worldwide). Active users are defined as those who have logged in at least once within the last 30 days [*www.statista.com*].

[4]In 2017, 15.79 million U.S. citizens lived in households that used an online investing/stock trading service within the previous twelve months (a 4.6% increase compared to 2016) [*www.statista.com*].

This increasing influence of social networks on everyday life and increasing reliance on online brokerage services has led to the emergence of new business models in recent years. Several online brokerage services combine the services of online brokerage with features of social networks. These services allow individuals to manage their portfolios and exchange capital-market-related information. In particular, these additional social network features enable investors to disclose and discuss their investment decisions with their peers. In the following, we will label these kind of brokerage services *social trading platforms*. Social trading platforms enable investors to share and obtain information and receive feedback on their trading decisions in large networks.[5]

By studying the trading behavior of investors who engage on a social trading platform, this study examines whether and if yes, how social recognition affects investors' trading patterns. We assess the magnitude of the influence of social recognition on investors' trading activity relative to the influence of confirmatory market feedback. Our results show that investors who receive social recognition for the first time subsequently execute 29 additional trades per month, on average, and 29 more trades per month, on average, than investors who do not receive recognition from their peers. We also confirm existing findings on the positive relationship between market outcome and investors' trading activity. Our study shows that increased trading behavior can be observed to the same extent for women and men, while young investors in particular seem to be less affected by social recognition. Our robustness checks show that social recognition also affects the trading activity of (i) the most successful investors, (ii) investors who use a buy-and-hold strategy, (iii) investors who have traded online for a long time, and (iv) those who trade frequently. Experiencing social and monetary confirmation simultaneously is associated with excessive levels of trading activity. However, in cases in which market feedback is unclear, social recognition expressed as positive social feedback seems to play a greater role in investors' future trading activity than monetary outcomes do. We investigate the causal influence of social recognition on investors' overconfidence with the help of an ex-

[5] Social trading platforms provide information that can be more accurate than assessments by professional analysts in some cases (Bagnoli et al., 1999; Clarkson et al., 2006; Doering et al., 2015). However, social trading platforms may not necessarily improve market efficiency: Han and Yang (2013) argue that social communication can result in endogenous information flow.

periment. Our experiment indicates that the psychological mechanism that explains the observed investor behavior is overconfidence and supports the notion that the increased trading activity is explained by investor overconfidence.

We contribute to the existing literature on behavioral finance by introducing social recognition as a driver of investors' trading patterns and a factor that influences how individuals behave in financial markets. In line with the theory of overconfidence and biased self-attribution, we show that after experiencing social recognition, investors tend to trade more often than they did before. Given its association with lower returns (Barber and Odean, 2000) and capital market overreactions (Daniel et al., 1998; Statman et al., 2006), overconfidence helps to illustrate individual investors' behavior and has implications for market efficiency. Therefore, we argue that social interaction may not contribute to market efficiency.

A growing strand of literature investigates the social dynamics on trading platforms and reports implications for financial markets.[6] For example, Ammann and Schaub (2016) show that investor communication within online networks (e.g., comments on investment decisions) influences the investment decisions of other traders. The frequency of communication, however, cannot be used to predict future return outcomes. Park et al. (2013) consider how investors value information obtained from their social environment and how this valuation affects their behavior and expectations. The authors report evidence that investors suffer from confirmation bias and argue that information that is in line with individuals' beliefs is valued more highly, whereas information that is at odds with investors' opinions is mostly ignored. As a result, investors' beliefs are reinforced, and their certainty—especially with respect to investment decisions—increases. In terms of outcomes, investors realize negative returns on average and do not outperform a well-diversified market portfolio when actively trading online or sharing information with their peers (see, e.g., Barber and Odean, 2000, 2002; Barber et al., 2006; Barber and Odean,

[6] For instance, Antweiler and Frank (2004) report that comments on stock message boards (e.g., Yahoo! Finance or Ranging Bull) contain predictive power for stock market volatility. In line with these findings, Chen et al. (2014) argue that social communication captures investor sentiment, which has significant effects on stock prices. Wang et al. (2015) find evidence that online communication has predictive power for stock returns. The authors show that online articles and comments by retail investors have explanatory power for stock returns.

2009; Pan et al., 2012; Oehler et al., 2016).

Our paper proceeds as follows. In Section 1, we explain the relationship between social recognition and overconfidence. We provide information on our dataset in Section 2. The results of our archival study are presented in Section 3. Section 4 presents our experimental study. We discuss our results and consider their implications in Section 5. The final section concludes.

# 1 Social interaction and overconfidence

Overconfidence associated with biased self-attribution helps to explain stock market return patterns that reflect irrational investor behavior (see, e.g., DeBondt and Thaler, 1985; Daniel et al., 1998; Thaler, 1999; Hirshleifer, 2001; Barberis and Thaler, 2003; Statman, 2014; Thaler, 2016).[7] The theoretical framework of overconfidence is based on two arguments. First, investors tend to overestimate their ability to identify valuable information that others miss. Second, investors are more likely to rely on self-generated information than on public information (DeBondt and Thaler, 1995; Odean, 1998; Daniel et al., 1998; Hirshleifer, 2001). Investors overestimate their ability to predict stock prices, make trading decisions based on personal assessments, and have favorable perceptions of their decisions. Overconfidence is even more pronounced for experts, and it increases with the degree of task difficulty (Fischhoff et al., 1977; Lichtenstein et al., 1982). The main consequence of overconfidence is increased trading activity, which has been introduced as a testable measure of investor overconfidence (Daniel et al., 1998; Gervais and Odean, 2001).[8]

In a multiperiod model, Gervais and Odean (2001) show that investors who are successful and consequently become wealthier face the risk of becoming overconfident. This argument centers on the cognitive bias of self-attribution, which causes the misinterpretation of new information (Bem, 1972; Rabin and Schrag, 1999). In experimental settings,

[7] DeLong et al. (1990) and Kyle and Wang (1997) provide evidence for the persistence of irrational investor behavior and show that irrational investors may also earn positive risk premiums.

[8] Glaser and Weber (2007) show that overconfidence is associated with higher trading activity.

psychologists have found empirical evidence that confidence is strongly influenced by the feedback that individuals receive regarding their past decisions (Wells and Bradfield, 1998) and that individuals tend to credit themselves for past success while blaming external factors for failure (Fischhoff and MacGregor, 1982; DeLong et al., 1991).[9] Specifically, individuals tend to attribute observed feedback that confirms the validity of their actions to their high level of ability, but they attribute feedback that is not in line with their decisions to external noise or sabotage. Consequently, in the case of biased self-attribution, feedback can lead to overreaction and cause investors to become overconfident.

In addition, people tend to make mistakes when they intuitively apply rules of statistics and probability (Paul and Lichtenstein, 1971; Tversky and Kahnemann, 1971; Kahnemann and Tversky, 1972) and are therefore inconsistent in their decision-making and judgment (Tversky and Kahnemann, 1981).[10] Individuals' judgment is driven primarily by the strength of supporting arguments for a certain hypothesis, but they exhibit poor consideration of the credibility of the source of these arguments (Tversky and Kahnemann, 1974; Dawes and Kagan, 1988; Griffin and Tversky, 1992). In particular, Griffin and Tversky (1992) show that when individuals change their confidence, they focus on the strength of observed feedback regarding prior decisions and underestimate its credibility. Strong feedback from an unreliable source is perceived as more valuable than weak feedback from a reliable source. As a result, an individual's level of confidence is determined by a trade-off between supporting and non-supporting arguments, while only some adjustments are made in response to their perceived credibility.[11] In the context of financial markets, observed feedback that has the same sign confirms a decision. As investors experience confirmation of their past decisions, their confidence increases; however, negative feedback triggers only a moderate or no decrease in confidence. The empirical finance literature has tested this hypothesis based on market returns. The results indicate that individuals attribute investment decisions that result in positive returns to their own

[9]In a more recent meta-analysis, Douglass and Steblay (2006) provide supporting evidence for the relationship between feedback and confidence.

[10]Tversky and Kahnemann (1981) also show that this phenomenon cannot be eliminated with monetary incentives.

[11]Griffin and Tversky (1992) show that people exhibit overconfidence when the magnitude of feedback is high but the validity of the source is low.

abilities to accurately evaluate securities. Conversely, investors blame bad luck and other external factors for trading losses.

We argue that social recognition has similar implications for investor overconfidence.[12] When investors interact with their peers (e.g., on trading floors, in social networks, or on the golf course) and discuss stock market developments, they also address past trades and their outcomes. Heimer and Simon (2013) and Han et al. (2017) argue that investors enjoy talking about success and thus are more likely to focus on profitable trades than on unprofitable trades. When sharing this type of information about past transactions, other investors provide feedback regarding investors' past trading decisions. When evaluating the observed social recognition, investors can gauge this feedback based on their peers' verbal or visual cues and sometimes even based on monetary stakes, e.g., when another investor indicates that he or she might use this information for a future transaction. However, it is very difficult to evaluate the credibility of the feedback provider. Individuals will tend to attribute positive social feedback to their ability to accurately evaluate securities. They may, however, also interpret disconfirming social feedback as ignorance, a lack of knowledge, or jealousy on the part of the feedback provider. As investors receive confirmatory social feedback regarding their past decisions, overconfidence increases; however, dissenting feedback leads to only a moderate or no decrease in overconfidence.

We argue that social recognition expressed as positive feedback has a significant effect on the overconfidence of capital market participants, leading them to increase their trading activity. Specifically, the level of overconfidence among investors increases and decreases in response to the feedback from their social environment regarding their past investment decisions. If investors receive social recognition, they tend to become overconfident and will trade more actively. However, in the case of a negative social response, investors' level of overconfidence shows only a moderate or no decrease.

Drawing on this and other insights in the literature, we aim to test the following set of

[12] Pirmoradi and McKelvie (2015) provide empirical evidence that people's level of confidence can be influenced by social feedback.

hypotheses. We argue that (i) investors increase their trading activity in response to confirmatory feedback from their social peers; (ii) simultaneously observing confirmatory market and social feedback is associated with an even greater increase in trading activity; (iii) the effect of social recognition is robust to investors' level of success and trading strategy; and (iv) investors tend to follow the signals of the highest magnitude and those that, in retrospect, confirm their decisions.

# 2 The social trading platform and data

Similar to market feedback, which can be measured by returns, we focus on social recognition that is directly related to investment decisions. To avoid inconsistencies with respect to the perceived validity and magnitude of feedback, which affect how individuals value this type of feedback, we rely on a quantified measure of social recognition. Specifically, we attribute confirmatory social recognition to an investment decision if that investment decision directly influences a transaction made by another investor. When traders invest their own money in response to an investment decision of another trader and thus place their own money at risk, they send a strong signal that confirms other investors' investment decisions. Thus, investors can interpret the triggered transaction as social recognition.

## 2.1 The social trading platform

We base our analysis on data obtained from a social trading platform. Similar to other online trading brokerage websites, this trading platform allows investors to complete various capital market transactions. In addition to permitting traditional financial services, a *disclosure* function allows investors to share and to keep track of capital market transactions executed by other investors on the trading platform.[13] This feature allows us

[13]Researchers have provided three main explanations for why investors share information with their social environment (see, e.g., Becker, 1974; Hong et al., 2004; Roa Garcia, 2013; Chen et al., 2014). First, word-of-mouth and observation of the actions of other traders allow investors to learn from others, e.g., how to trade or evaluate information and to participate in financial markets. Seen in this light,

to analyze the implications of social recognition for investor trading behavior. Traders can communicate about and follow others' transactions. Investors' performance in the previous year and on the last trading day and a *follow* function are provided at first glance. On individual profile pages, traders are able to communicate with others by posting messages, which can be highlighted, commented on, or shared by other traders.

Detailed information on each investor's trading activity can be obtained from four different sections. First, the statistics section provides a detailed overview of investors' historical performance, risk-taking, social recognition, and trading activity. Other traders can review past monthly and annual returns, the number of total trades executed, the proportion of different asset classes, and the percentage of profitable outcomes. The website also provides a historical risk level, which tracks an investor's leverage and the volatility of his or her investments compared to the volatility of the markets in which s/he trades. More important for this study, the statistics section likewise offers detailed information on investors' received social recognition: people can review how many investors currently follow the transactions of a particular trader. The social chart shows the historical development of followers over the past year, whereas the social trend indicates the relative change in followers over the last seven days. Additional statistics, such as the average trades per week or an investor's average holding period, are provided at the bottom of the page. The portfolio section provides a detailed overview of the current portfolio, including a list of the individual securities, their shares in the overall portfolio, their performance, and their current bid and ask price. In the graph section, historical performance is visualized in a time-dynamic chart.

To follow another trader, people can click a *follow* button at the top of each investor's profile page. They can define how much money they intend to invest when following the positions and have the opportunity to set a stop-loss price.[14] Consequently, people who

social interaction is likely to facilitate the process of learning and gathering information, and investors may believe that they make better investment decisions after talking to their peers. Second, people may enjoy talking about market movements with their peers in the same way that they enjoy talking about restaurants, sports, or other topics. Third, as mentioned before, investors may gain utility from the attention and recognition they receive from their peers. The argument that investors exchange information because they are motivated by the opportunity to learn or to increase their utility through communication or recognition may also explain why social interaction affects investor behavior.

[14]Similar to professional fund managers, traders who are being followed by other investors and manage

copy an investment made by another trader entrust a proportion of their wealth to the decisions of another investor. Therefore, we argue that people who copy the transactions of others signal a high level of recognition to the investors they follow as they are placing their own money at risk. Since investors seek to earn money, we argue that following a trader can be seen as a disclosed prediction that the investor can execute profitable trades in the future. Moreover, investors will receive information on how many other traders have followed their investment decisions. By being aware of the financial commitment of their followers, investors can interpret the number of traders who follow them as the magnitude of their social recognition. Specifically, investors may attribute a level of social recognition to their past trading activity. As the magnitude of social recognition increases, traders' past investment decisions are more strongly confirmed. Moreover, investors observe a standardized indicator of social recognition and are therefore able to compare their level of social recognition with that of other investors or their own history. These data on individual investors allow us to study the implications of social recognition for investor trading behavior.

## 2.2 Data

The focus of our analysis is the change in trading behavior after investors receive social recognition. Our dataset comprises 72,245 unique individuals who engaged in online trading for at least five months during the period from January 2012 to October 2015. Of these investors, 21,694 received social recognition at least once during that period and executed 12.4 million trades. In total, the group of investors who receive social recognition at least once comprises 284,058 investor-months. The data provide detailed information on all transactions and related social recognition. On a monthly basis, we analyze investor-specific trades, realized returns net transaction costs, the number of followers, portfolio diversification, the holding period of positions, the number of different

others' capital receive some monetary compensation from the brokerage service in relation to the assets under management.

securities traded, the number of other investors followed, and the use of leverage.[15]

- Place Table 1 about here -

We determine the average returns, number of executed trades, holding period, level of diversification, number of traders followed, and instruments used for each individual investor and differentiate between those investors who receive social recognition and those who do not. Panel A of Table 1 reports basic summary statistics of the different investor groups in our dataset across five independent return groups. Overall, investors who receive social recognition trade more often than those who do not across all different return groups. The investors in the highest return quintiles exhibit the lowest trading activity in their investor group on average (22.93 [10.46] trades executed by investors who [never] received social recognition). These investors also exhibit the highest average holding period in their investments. In line with the literature on online trading, investors lose money on average as they trade online (see, e.g., Barber and Odean, 2002; Pan et al., 2012). Only 22.06% of those investors who never receive social recognition earn positive overall returns, whereas only 15.19% of all investors who receive social recognition gain money. Moreover, investors who receive social recognition have lower average holding times for their trading positions, are more diversified, and have more faith in other investors. We provide a more detailed multivariate analysis in the following sections.

Panel B of Table 1 illustrates the distribution of investors in our sample across gender and age. We report demographic information for the full sample and for investors who receive social recognition and those who do not separately. We observe that our sample contains more than five times more male investors than female investors. Moreover, the table highlights that our sample contains a large number of young investors.

[15] Trades are the number of executed trades in a particular month; return is the average return realized in a month net transaction costs; follower represents the number of other investors who have followed investors' trades; portfolio diversification is a dummy variable that equals one if no single open position exceeds 20% of an investor's overall capital and zero otherwise; holding position represents the average number of hours that the investor keeps each position open; the number of instruments is the number of different securities that the investor traded in a particular period; and leverage is a dummy variable that takes the value of one if a trader has any leveraged position in his portfolio, and zero otherwise. Following others represents the number of other investors that a trader is currently following.

Based on the demographic information, we generate two dummy variables. In particular, we generate a dummy variable *Male* taking the value of one if the investor is male and zero otherwise and a dummy variable *Young* taking the value one if the investor is 34 years or younger and zero otherwise.

# 3 Social recognition and trading activity

Our analysis is divided into two parts. First, we study the change in the trading behavior of investors who receive social recognition relative to that of investors who do not receive social recognition. We employ a difference-in-differences approach for our analysis. Second, we conduct a thorough analysis of the effects of social recognition on trading activity for investors who experience confirmatory social feedback. This step allows us to study the implications of monetary and social feedback for investors' trading activity.

## 3.1 Does social recognition cause a change in trading behavior?

To investigate whether investors change their trading behavior in response to social recognition of their investment decisions, we conduct a difference-in-differences analysis. Our treatment group comprises all investors who receive social recognition about their investment decisions, while our control group comprises those investors who do not receive social recognition. The treatment event, namely, the first time that at least one investor follows the trading decision of another investor with his or her own money, can occur at any point in time. We perform nearest-neighbor matching to match investors in the treatment and control groups based on gender and age range and on criteria that constitute similar trading activity, similar realized returns, similar position holding periods, a similar number of instruments used, similar levels of leverage, and a similar number of other investors followed as proxy for sociability prior the treatment event. We exclude investors for which we cannot find a match in our data from the analysis. For our main analysis, our matched sample consists of 19,777 investors from the treatment group and 19,777 investors from the control group. We differentiate among different treatment effects and study their implications. The different treatment effects are (i) the first instance of social recognition, (ii) the second instance of social recognition, and (iii) the first instance of social recognition combined with simultaneous positive market feedback. For each treatment, we perform a separate matching. In our estimations, we control for investors' past profitability, their holding periods, the number of instruments used, the level of leverage, the degree of diversification, and the number of other investors followed. Additionally, we include dummy variables to identify male and young investors.

- Place Table 2 about here -

Table 2 reports the results of our difference-in-differences estimation. We observe positive significant average treatment effects (ATE) and average treatment effects on the treated (ATET) in the month following the treatment event in all three cases. On average, investors execute 29.05 more trades in the month after they receive social recognition for the first time than do traders in the control group (Panel A, Model (1)).

As Barber and Odean (2001) and Forbes (2005) report that age and gender are significant determinants of overconfidence and young men's behavior is particularly affected by this psychological bias, we next investigate the influence of gender and age on the influence of social recognition on trading activity. In particular, in Model (2) we observe a similar treatment effect for male and female investors. Male investors do not seem to be particularly prone to changes in their trading behavior following social recognition. However, Model (3) indicates that young investors seem to be less affected by social recognition. The negative interaction term indicates that young investors increase their trading behavior to a significantly smaller extent than other investors do. To be specific, investors who are 34 years or younger execute 25.08 more trades in the month after they receive social recognition for the first time. Models (4) and (5) present ATE for our additional treatment specifications.

Panel B of Table 2 reports simulated ATET. Investors increase their trading activity and execute 29.05 more trades per month on average than they did before receiving social recognition. Our results are robust to three different treatment specifications. Investors increase their trading activity after receiving (i) social recognition for the first time, (ii) social recognition for the second time, and (iii) confirmatory social and market feedback simultaneously. Thus, social recognition causes an increase in investors' trading activity.

## 3.2 Returns, social recognition, and trading activity

In the second part of our analysis, we apply additional sorting and panel data regressions to investigate the relationship between received market and social feedback and trading activity. For each investor, we identify the periods before and after receiving social recognition for the first time. Moreover, we independently rank all periods by the realized returns for each investor and assign them to five groups (low-return-months to high-return-months).

- Place Table 3 about here -

Table 3 reports the results of a two-way sorting approach on the treatment event (pre- and post-social recognition) and realized return-months. In line with our previous results, investors complete, on average, more trades in months after experiencing social recognition. The highest increase in trading activity (9.03 to 10.96) is recorded for months when investors realize slightly negative (Return-3) to slightly positive (Return-4) returns. In these months, the observed market feedback is of low magnitude, and strong confirmatory social recognition seems to have a larger effect on investor trading activity. In months when investors realize their worst outcomes, i.e., when market feedback is strongly negative, investors decrease their trading activity. We also observe that in months with low return outcomes, investors increase their average position holding period in the post-treatment month. Investors also tend to follow fewer other investors after receiving social recognition.

Table 4 presents the pairwise correlation coefficients between all variables of interest. The correlation between follower, return, and executed trades is low. Unsurprisingly, investors' position holding periods are negatively correlated with the use of leverage. In addition, the number of different securities held is positively correlated with following other investors' investment decisions.

- Place Table 4 about here -

To further investigate the relationship between social recognition and investor trading activity, we perform a set of panel data regressions on the sample of investors who receive social recognition. We control for investor and time fixed effects and use robust standard errors clustered at the investor level to control for heteroskedasticity and serial correlation. Our dependent variable, the log number of trades executed by investor $i$ in month $t$, captures traders' individual trading activity. Our variable of interest is the magnitude of social recognition (Follower), that is, the log of number of traders who followed investor $i$ in month $t-1$. As the number of followers increases, the magnitude of social recognition increases. We lag all independent variables by one period to capture behavioral patterns after experiencing a change in social recognition and to avoid potential endogeneity problems.

- Place Table 5 about here -

Table 5 reports the results of our main analysis. In Model (1), we observe a positive and significant coefficient on Follower (0.198, $p < 0.01$). This result indicates that social recognition is associated with an increase in investors' trading activity in the next period and underlines the findings of our difference-in-differences analysis. Next, we control for past trading performance (return), trading activity, average holding period, investor sociability, and the type of portfolio (leveraged or diversified). Model (2) presents the coefficients for Follower and all the control variables we consider in our analysis. A positive and significant coefficient on Follower (0.017, $p < 0.01$) confirms the positive and significant relationship between social recognition and trading activity in the following period. In Model (3), we investigate the interaction between past performance and social recognition. In particular, we aim to examine investors' behavior after observing simultaneous market confirmation (positive returns) and social recognition (an increasing number of followers). The significantly positive interaction coefficient (71.45, $p < 0.01$) indicates that investors increase their belief in their own trading abilities to an even greater extent after simultaneously observing a high magnitude of social and market confirmation.

In our next step, we examine the interaction effects of social and market feedback in greater detail. In particular, we investigate controversial observed outcomes with respect to market and social feedback. In Model (4), we replace investors' continuous past returns with a profit dummy variable (Profitable) that equals one if an investor's return was positive and zero otherwise. We also replace continuous social confirmation with a dummy variable (Follower Decrease) that equals one if the trader experienced a decrease in followers in this period and zero otherwise. Our analysis reveals a positive (negative) and significant relationship between the Profitable (Follower Decrease) dummy variable (0.230, $p < 0.01$; $-0.132$, $p < 0.01$) and trading activity. Investors tend to trade more actively after making profitable trades and less actively after losing social recognition. A smaller but significantly positive interaction coefficient (0.081, $p < 0.01$) indicates that market confirmation has stronger effects on trading activity than do social responses but that disconfirming social feedback attenuates the increase in trading activity.

To study the counterpart to the interaction, we replace investors' past mean return with a loss dummy (Unprofitable) that equals one if a trader's past return was negative, and zero otherwise, in Model (5). We measure social recognition as a dummy variable (Follower Increase) that equals one if the trader experienced increasing followers in this period and zero otherwise. Our regression results indicate a negative (positive) coefficient for the Unprofitable (Follower Increase) dummy ($-0.234$, $p < 0.01$; 0.037, $p < 0.01$). After experiencing trading losses, investors tend to trade less, whereas an increase in social recognition has a positive influence on investor trading activity. A significantly negative interaction coefficient ($-0.087$, $p < 0.01$) indicates that investors value monetary outcomes over social recognition. Investors who experience an increasing number of followers associated with monetary losses tend to execute fewer trades in the following period.

## 3.3 Investors' trading characteristics and social recognition

Next, we investigate how investors with different trading outcomes and trading strategies respond to social recognition. The summary statistics presented in Table 1 indicate that investors who realize positive overall returns exhibit the lowest trading activity in their respective groups. Successful investors who trade less might not systematically change their behavior after receiving social recognition. We conduct a subsample analysis with only those investors who are successful traders. Specifically, we consider all investors who realize positive overall returns. In addition, we examine those investors who, on average, exhibit the longest holding period for their positions, i.e., the buy-and-hold investors in our sample period. Moreover, we examine investors who have the longest history, i.e., at least 30 months of trading in our 46-month sample period. Finally, we examine those investors who, on average, show the highest number of executed trades per month.

- Place Table 6 about here -

Our results presented in Table 6 show that the relationship between social recognition and trading activity is robust to the various specifications. The results indicate that social recognition is associated with increasing trading activity in the following month for (i) successful investors (winner), (ii) investors who pursue a buy-and-hold strategy (buy-hold), (iii) investors who trade for a long time (long term), and (iv) investors who tend to execute the most trades per month on average (frequent). A positive and significant coefficient on Follower in all subsample regressions confirms our previous results and shows that social recognition is indeed associated with increased trading activity in the future.

## 3.4 The magnitude of observed social recognition

Next, we apply an additional two-way sorting procedure to investigate the relationship between observed return, social recognition, and trading activity. For each investor, we independently rank all months with respect to realized returns and the magnitude of social recognition. We allocate all months to five return groups (low-return-month to high-return-month) and into three social recognition groups (weak, medium, and strong). This approach results in 15 return-social recognition intersection months. We consider months with relatively low realized returns and relatively weak social recognition compared with months with high realized returns and strong social recognition.

- Place Table 7 & Table 8 about here -

Table 7 reports the results of our sorting procedure. One month after receiving strong social recognition, investors exhibit increased trading activity. Except for the months with the highest realized returns, investors' trading activity increases with higher observed returns. On average, investors realize positive online trading returns in 40% of the months in our sample period. Especially in periods with ambiguous market outcomes (Return month-2 to Return month-4), social recognition is associated with an increase in trading activity. This result holds in particular in months in which investors receive the strongest social recognition. Table 8 provides more detailed information on the return distribution across investors' 15 intersection months and shows that some investors realize just slightly negative returns while some investors realize no positive returns in their worst and best months. Finally, Table 7 provides additional information about the realized returns one period after the sorting procedure. The results indicate a reversal pattern in individual investor returns, which is in line with existing empirical studies on the implications of investor overconfidence (see, e.g., Barber and Odean, 2001; Choi et al., 2002; Grinblatt and Keloharju, 2009). More precisely, investors who realized positive returns in period $t$ experience losses on average in the following period $t + 1$.

## 3.5 Peer comparison and social recognition

Our investigation shows that investors change their trading activity depending on observed social recognition over time. However, within social communities, i.e., on social trading platforms, investors can observe not only their own social recognition but also the responses that other individuals receive from the social community. In particular, investors can monitor other investors' level of social recognition as the number of traders following them. Individuals cannot only keep track of their own level of social recognition but also compare themselves with other peers. In other words, investors cannot only observe the evolution of feedback over time but also in the cross section and *compete* with other investors. In a related context, literature provides evidence for the relevance of cross-sectional competition in the mutual-fund market (see, e.g., Brown et al., 1996; Busse, 2001, on tournaments in the mutual-fund market). Consequently, the level of social recognition in comparison within the social community might also affect how investors' confidence is influenced by social recognition.

In this section, we conduct an additional sorting procedure to assess the effect of social recognition in the cross-section of investors. Each month, we sort all investors based on their number of followers and realized returns. We separate groups for investors with top 10%, 20%, and 50% of social recognition at each point in time to investigate the implications of absolute ranking within the social community. In addition, we investigate how trading activity and realized returns change if an investor's position in the social community changes compared to the previous period. In order to do so, we generate a dummy variable that is equal to one if the investor switches to a group of higher social recognition than in the previous month and zero otherwise. Furthermore, in each month, we allocate investors into five return groups (low-return to high-return).

- Place Table 9 about here -

Table 9 provides the results of our two-way-period-based sorting. Our results indicate that the absolute rank within the social community does not affect investors' trading activity. However, if investors move into a higher social recognition group, i.e., from the top 20% to the top 10% of investors, they increase their trading activity in the next period on average. Interestingly, we observe these effects only for investors who are in the top three return groups. On the other hand, even if investors significantly improve their position in the social community with respect to the recognition of their peers, when combined with negative realized returns, they do not increase their trading activity.

# 4 Social recognition and investor confidence

Motivated by the empirical findings of our archival study, we conduct a laboratory experiment to shed more light on the more pronounced trading activity of investors who receive social recognition. Laboratory experiments offer controlled environments to study subjects' emotions and preferences which can help to better understand the emergence of decision biases. Thus, the experiment allows us to isolate the underlying psychological mechanism that explains the observed investor behavior.

Our archival study presents robust evidence that social recognition triggers an increase in active trading activity. We hypothesize that the finding can be explained by overconfidence. However, there may also be other possible explanations for our results. First, individual investors who rely on more than one brokerage service may not increase their trading activity but instead shift a proportion of trades previously executed by other brokerage services to the trading network. Specifically, individual investors may not trade more but shift between service providers. Another possible explanation relates to the fact that traders who are being followed by other investors receive monetary compensation if they manage others' capital. Similar to professional fund managers, investors receive compensation for their assets under management, an incentive to increase the number of following investors and increase one's assets under management. Investors could simply aim to maximize their followers and assets under management instead of seeking profitable investment decisions. However, our results show that the actual trading outcome still has a greater influence on investors' trading activity than social recognition in most cases. Observing adverse outcomes of investments is associated with lower trading activity in the next period even though the trader simultaneously receives social recognition. Finally, similar to Barber and Odean (2002), we may face the risk of sample selection bias. Social trading platforms simplify the process of information exchange and encourage trading activity. Consequently, social traders may more likely be overconfident.

In order to address these alternative explanations for our results, we conducted a computer-based lab experiment with 66 students from University of Lüneburg to test the hypothesis that social recognition increases investors' overconfidence.[16] During the experiment, participants invested fictional money on a simulated online trading platform. While we provided participants in the experimental group with social recognition for their trading behavior, we did not give any social information to participants in the control group.

## 4.1 Experimental procedures

To test the causal effect of social recognition on investor overconfidence, we created a simulated trading platform with the help of oTree (Chen et al., 2016). On the platform, participants played five investment rounds in which they could invest 10,000 Euros of fictional money in three different stocks from different companies per round. For each participant and round, the stocks were randomly drawn from a selection of 30 different stocks. We changed the name of the companies and excluded well-known companies in order to avoid biases due to participants' prior background knowledge.[17] Participants received fundamental information on the different stocks including the current price of the stock, intraday change, and basic information on the company. An example of the information provided to participants can be found in the Appendix (Figure A1). Participants could decide to either not invest, or invest in one or several of the stocks any fraction of their fictional wealth. After every round, participants specified their level of confidence in making profitable investment decisions. Then, participants received feedback on their new level of wealth resulting from the performance of the stocks they had invested in.

In the experimental group, we provided participants with social recognition. In order to provide participants with social recognition, we displayed a notice such as "3 observers have decided to entrust you a total of 16,400 Euro". Between participants, we altered

[16] In fact, 69 participants took part in our experiment. However, one participant did abort the study and two participants did not supply demographic information.

[17] In a control question after the experiment no participant indicated that s/he has recognized any of the companies.

the number of observers and the total amount between one and three observers and 5,400 and 16,400 Euro. The first time participants received social recognition was after the conclusion of the third round (i.e. after participants had entered their confidence level regarding their investment decisions of the third round). To lend credence to the social recognition in the experimental group, participants were told that the experiments simultaneously took place at another university. Participants were told that a number of students from the second university had also been given a fixed amount of 10,000 Euros of fictional money to invest. Additionally, it was said that the participants from the second university were able to track the participants' investment decisions and could decide whether they wanted to follow their investment decisions or rather invest their money on their own. Importantly, participants were told that the participants from the other university could only observe their investment decision but not their replies to any other questions. To lend credence to the simultaneous observation and investment of participants from the second university, participants could only submit their investment decisions between ten and twelve minutes after the stock presentation and had to wait another two minutes after their decision to give their alleged observers time to examine their investment decisions.

In the control group, participants received no social feedback of any kind after their investment decisions and were not told that any kind of feedback was possible or given to other participants. However, participants in the control group were also told that the experiments simultaneously took place at another university. To hold the conditions between the experimental and the control group as constant as possible, participants in the control group also had to submit their investment decisions between ten and twelve minutes after the stock presentation.

Our platform was pre-tested by eleven experts in online trading and experimental research.

The experiment took place in the university's computer lab. Visual covers between the computers were installed to avoid distraction by other participants' screens. We recruited students with the help of SonaSystems, a cloud-based participant management platform which allowed us to contact registered students from our target university. As we conducted our experiment in English, we specified that we were looking for participants with basic English proficiency to ensure participants could follow the instructions. We also communicated a general knowledge about and interest in financial markets as inclusion criterion. All participants received a performance-based compensation to assure they would do their best in their investment decisions. Participants earned 14.88 Euros, on average. Participants could register for different time slots with a maximum of 15 participants per time slot. In total, seven sessions were conducted. Participants in each session were randomly assigned to either the treatment or the control group.

The experiment lasted 90 minutes per session. After entering the lab, participants were welcomed by reading out a written introduction informing about the duration of the experiment and the payment procedure. Then, the experimenter told all participants that the experiments simultaneously took place at another university. She subsequently pretended to call a colleague at this university, telling the colleague that the experiment could begin in one minute.

In the following, participants started to read and sign a written consent form. As revealing the actual overall goal of the experiment would cause potential bias in the participants' behavior, participants were informed that the study goal was to find out about students' performance in comparison to expert performance regarding investment decisions.[18] After that, participants read the instructions of the experiment. Instructions for both groups were identical except from the additional information on potential followers from the second university in the experimental group. A short questionnaire asking for participants' level of stock market experience and confidence in making stock picks followed the instructions in both study groups. Subsequently, participants started to invest in the stocks in five investment rounds. After having played all rounds, participants completed a lottery choice procedure from Holt and Laury (2002) and filled in a final questionnaire asking for basic demographic information.

Before participants left the room, they were presented a detailed debriefing informing

[18]The use of deception was previously approved by the ethics board of Paderborn University.

them about the true underlying study goal and providing contact information in case of possible further questions. In a last step, participants received their remuneration through a third person. To assure the anonymity of participants' data, the person responsible for the remuneration did not have access to the study data and the authors did not have access to the renumeration data with participants' names.

## 4.2 Measures and variables

We measured confidence—our dependent variable—before the investment rounds and after each investment round with the help of a one-item measure based on Weber and Brewer (2003). Specifically, we asked *How confident are you that your investment decision will be profitable?* Answers were rated on a 11-point Likert scale capturing the percentage to which participants felt confident in the profitability of their investment decisions (1=0%; 11=100%).

We create several variables to indicate the treated participants. First, *Treatment* is a dummy variable that takes a value of one if the participant is in the treatment group, zero otherwise. Additionally, *Follower* denotes the number of observers indicated in the treatment messages (i.e., the number of participants of the second university that allegedly followed a participants investment decisions). Finally, *AUM* indicates the Euro amount that participants were told was entrusted to their investment decisions in the treatment message.

We create a variable Return denoting the return on investment participants earned on their investment decisions. Subjects' risk aversion was elicited using a lottery choice procedure from Holt and Laury (2002). Subjects also answered a brief demographic survey, indicating their English proficiency and stock market experience measured on 7-point Likert scales, their gender, age, and their study background.

## 4.3 Results

We begin the description of the results from our experimental study by discussing some descriptive statistics. In total, 66 of our participants completed the experiment.[19] 50% of the participants were female. Their mean age was 21.5 years and their mean level of self-assessed English proficiency was 5.5. 27% of our participants major in Finance. Their mean level of stock market experience was 3.6. In the lottery choice procedure from Holt and Laury (2002), the participants on average switched between lotteries five and six.

To study the impact of our treatment on participants confidence levels in a multivariate setting we employ ordinary least squares regression. For the treatment group, the treatment takes place after the third round of investment decisions. Therefore, our dependent variable is the change in participants' confidence between the third and fourth period. Our variable of interest is Treatment. As additional independent variables, we include participants return on investment from their investment decisions in the third period; participants risk aversion; participants gender as a dummy variable that takes a value of one if the participant is male, zero otherwise; participants age; and their level of stock market experience.

- Place Table 10 about here -

Results of our OLS regressions are presented in Table 10. Model (1) indicates that receiving social recognition increases participants confidence levels. Moreover, our results indicate that a higher degree of risk aversion is associated with higher levels of confidence. A possible explanation may be that participants who are more risk averse are more careful with their investment decisions and as a result more confident with their choices. In Models (2) and (3) we replace our treatment dummy with *Follower* and *AUM*, respectively. The results support our hypothesis that social recognition increases participants' confidence levels.

In additional (unreported) investigations, we analyze whether the treatment effect differs between male and female participants, with respect to different degrees of risk aversion,

[19] One participant left the laboratory early and two participants did not supply demographic information.

or with participants' level of stock market experience using interaction terms. In our sample, we do not observe any moderating effects of these variables.

The results of our randomized controlled experiment indicate an increase in investors' confidence level subsequent to receiving social recognition. This supports the notion that investor overconfidence is the mechanism responsible for the increased trading activity of investors after receiving social recognition for the first time.

# 5 Discussion and implications

The aim of our study is to answer the question of whether social recognition influences investors' trading activity. Our results show that confirmatory social feedback—social recognition—causes investors to increase their trading activity. Specifically, our findings indicate that investors incorporate feedback from their social environment when updating their level of confidence in their ability to accurately evaluate stock prices. Our results can be explained by overconfidence, biased self-attribution, and misinterpretation of observed feedback.

Our study makes two important contributions to the literature on behavioral finance. First, we provide empirical evidence that suggests that social interaction may not increase market efficiency. Feedback provided by investors regarding a past trading decision of another investor is unlikely to contain any relevant information for future stock prices. This feedback should not have any effect on the future investment decisions of rational investors. Consequently, increased trading activity caused by social recognition does not contribute to stock price efficiency.

Second, our results indicate that social recognition increases investor overconfidence. This increase can be explained by biased self-attribution and low attention devoted to the credibility of the source of feedback. Changing behavior due to overconfidence has been identified as a reason for the non-persistence of investor returns. Understanding the influence of social recognition on overconfidence will help researchers to understand why investors overestimate their ability to accurately evaluate information and to predict future stock prices and why they consequently lose money.

Additionally, our results suggest that online social recognition has a similar impact on males and females and a lower impact on young individuals. This finding contradicts other studies on overconfidence (see, e.g., Barber and Odean, 2001; Forbes, 2005) but could be explained by the specific nature of interactions on social media. In particular, the younger generation may be more accustomed to interactions on social media because they have grown up in a society increasingly reliant on social media, and as a result, they may be less affected by online social recognition. Nonetheless, in our study, the younger generation proved to be significantly affected by social recognition, executing 25 additional trades in the month after receiving social recognition for the first time.

Our results have implications for investors who interact with their social environment, seek information from their peers, and receive social recognition. While being aware of their behavioral biases, investors should be cautious when they share the outcomes of their past trading decisions with their social environment because past trading activity does not provide relevant information for future market prices. Utility gains due to social recognition should be considered carefully. Social recognition allows for conscious or unconscious manipulation by peers. However, investors engage in social interactions to seek information and learn from others and ultimately make better investment decisions. Nevertheless, those investors should be aware of the signals that they send to their peers once they begin to follow others' information or investment decisions.

In other contexts, such as yelp.com (e.g., for restaurants) or amazon.com (e.g., for books), social recommendations seem to be a valid indicator of high-quality goods or services. Therefore, people increasingly rely on the recommendations and evaluations of their peers and have begun to apply peer advice systems to financial markets. Investors seek to identify other investors who earn the highest profits and share the most profitable trades. Given the assumption that investors who follow other traders' transactions still seek to earn positive returns, having many followers can be interpreted as an indicator of high reputation and trading skill. In the context of financial markets, investors should be cautious when they rely on traders who are recommended by their peers for two reasons. First, traders who already observe a large magnitude of social recognition may act in an overconfident manner. Second, following those investors' trading decisions is an additional signal of social recognition. When traders receive social recognition for the first time, the influence on their level of confidence is even greater, which can cause changes in investors' behavior and adversely affect trading performance. Social trading platforms allow investors to receive feedback on their past trading decisions with the objective of offering their clients more efficient communication and participation in financial markets. Due to social dynamics and individual cognitive biases, some of the decisions made by investors may be even worse than they would have been without such a service.

# 6 Conclusion

This study has three important findings. First, observing social recognition increases investors' trading activity and confidence level. Second, positive monetary and social feedback is associated with even greater trading activity in the future. Third, when market outcomes are unclear, social recognition has a greater effect on investors' trading activity. Our results are robust to different investor characteristics and trading outcomes. These findings are consistent with the theory of overconfidence and biased self-attribution. Investors attribute confirmatory feedback from their peers to their high ability to predict stock prices. In addition, people focus on the magnitude of signals and devote less attention to the credibility of the source of information. Due to this cognitive bias, information exchange between social peers does not necessarily increase market efficiency.

Social interaction has been identified as a relevant factor of human behavior, and increasing opportunities for information exchange are likely to increase the intensity of social interactions, which has implications for human behavior. Online networks enable researchers to study the behavioral patterns of individuals within social groups and to shed light on the influence of social interaction on investor behavior. We study the consequences of social recognition as part of the interaction within peer groups and thereby contribute to the literature on behavioral finance and investor behavior.

However, there is room for further research to better understand the relationship between social interrelations and human behavior in financial markets. It remains unclear whether social dynamics have implications for overall market prices. Further research may also investigate how social interaction influences emotions and trust between investors and how this may play a role in decision-making related to financial markets.

# References


Ammann, M. and N. Schaub (2016): "Social Interaction and Investing: Evidence from an Online Social Trading Network," *Working Paper*.

Antweiler, W. and M. Z. Frank (2004): "Is All That Talk Just Noise? The Information Content of Internet Stock Message Boards," *Journal of Finance*, 59, 1259–1294.

Bagnoli, M., M. D. Beneish, and S. G. Watts (1999): "Whisper forecasts of quarterly earnings per share," *Journal of Accounting and Economics*, 28, 27–50.

Barber, B. M., Y.-T. Lee, Y.-J. Liu, and T. Odean (2006): "Just How Much Do Individual Investors Lose by Trading," *Review of Financial Studies*, 22, 609–632.

Barber, B. M. and T. Odean (2000): "Trading Is Hazardous to Your Wealth: The Common Stock Investment Performance of Individual Investors," *Journal of Finance*, 55, 773–806.

——— (2001): "Boys Will be Boys: Gender, Overconfidence, and Common Stock Investment," *The Quarterly Journal of Economics,*, 116, 261–292.

——— (2002): "Online Investors: Do the Slow Die First?" *Review of Financial Studies*, 15, 455–487.

——— (2009): "Too many cooks spoil the profits: The performance of investment clubs," *Financial Analyst Journal*, 56, 17–25.

Barberis, N. and R. H. Thaler (2003): "A Survey of Behavioral Finance," *Handbook of the Economics of Finance*, 1, 1053–1128.

Becker, G. S. (1974): "A Theory of Social Interactions," *The Journal of Political Economy*, 82, 1063–1093.

Bem, D. J. (1972): "Self-Perception Theory," *Advances in Experimental Social Psychology*, 6, 1–62.

Brown, J., Z. Ivkovic, P. Smith, and S. Weisbenner (2008): "Neighbors Matter: Causal Community Effects and Stock Market Participation," *The Journal of Finance*, 63, 1509–1531.

Brown, K. C., W. V. Harlow, and L. T. Starks (1996): "Of Tournaments and Temptations: An Analysis of Managerial Incentives in the Mutual Fund Industry," *The Journal of Finance*, 51, 85–110.

Burks, S., J. P. Carpenter, L. Goette, and A. Rustichini (2013): "Overconfidence and Social Signalling," *The Review of Economic Studies*, 80, 949–983.

Busse, J. A. (2001): "Another Look at Mutual Fund Tournaments," *The Journal of Financial and Quantitative Analysis*, 36, 53–73.

Chen, D. L., M. Schonger, and C. Wickens (2016): "oTree—An open-source platform for laboratory, online, and field experiments," *Journal of Behavioral and Experimental Finance*, 9, 88 – 97.

Chen, H., P. De, Y. J. Hu, and B.-H. Hwang (2014): "Wisdom of Crowds: The Value of Stock Opinions Transmitted Through Social Media," *Review of Financial Studies*, 27, 1367–1403.

Choi, J. J., D. Laibsona, and A. Metrick (2002): "How does the Internet affect trading? Evidence from investor behavior in 401(k) plans," *Journal of Financial Economics*, 64, 397–421.

Clarkson, P. M., D. Joyce, and I. Tutticci (2006): "Market reaction to takeover rumour in Internet Discussion Sites," *Accounting and Finance*, 46, 31–52.

Cohen, L., A. Frazzini, and C. Malloy (2007): "The small world of investing: Board connections and mutual fund returns," *Journal of Political Econom*, 116, 951–979.

——— (2010): "Sell-Side School Ties," *The Journal of Finance*, 65, 1409–1437.

Crawford, S. S., W. R. Gray, and A. E. Kern (2017): "Why Do Fund Managers Identify and Share Profitable Ideas?" *Journal of Financial and Quantittive Analysis*, 52, 1903–1926.

Daniel, K., D. Hirshleifer, and A. Subrahmanyam (1998): "Investor Psychology and Security Market Under and Overreactions," *The Journal of Finance*, 53, 1839–1885.

Dawes, R. M. and J. Kagan (1988): *Rational choice in an uncertain world*, Harcourt Brace Jovanovich.

DeBondt, W. F. M. and R. H. Thaler (1985): "Does the Stock Market Overreact," *The Journal of Finance*, 793–805.

——— (1995): "Financial Decision-Making in Markets and Firms: A Behavioral Perspective," *Handbooks in operations research and management science*, 9, 385–410.

DeLong, J. B., A. Shleifer, L. H. Summers, and R. J. Waldmann (1990): "Noise Trader Risk in Financial Markets," *Journal of Political Economy*, 98, 703–738.

DeLong, J. B., A. Shleifer, L. H. Summers, and R. J. Wladmann (1991): "The Survival of Noise Traders in Financial Markets," *The Journal of Business*, 64, 1–19.

Doering, P., S. Neumann, and S. Paul (2015): “A Primer on Social Trading Networks - Institutional Aspects and Empirical Evidence,” *Working Paper*.

Douglass, A. B. and N. Steblay (2006): “Memory Distortion in Eyewitnesses: A Meta-Analysis of the Post-identification Feedback Effect,” *Applied Cognitive Psychology*, 20, 859 – 869.

Duflo, E. and E. Saez (2002): “Participation and investment decisions in a retirement plan: the influence of colleagues’ choices,” *Journal of Public Economics*, 85, 121–148.

——— (2003): “The role of information and social interactions in retirement plan decisions: Evidence from a randomized experiment.” *Quarterly Journal of Economics*, 118, 815–842.

Fischhoff, B. and D. MacGregor (1982): “Subjective confidence in forecasts,” *Journal of Forecasting*, 1, 155–172.

Fischhoff, B., P. Slovic, and S. Lichtenstein (1977): “Knowing with Certainty: The Appropriateness of Extreme Confidence,” *Journal of Experimental Psychology*, 3, 552–564.

Forbes, D. P. (2005): “Are some entrepreneurs more overconfident than others?” *Journal of Business Venturing*, 20, 623–640.

Georgarakos, D. and G. Pasini (2011): “Trust, sociability and stock market participation,” *Review of Finance*, 15, 693–725.

Gervais, S. and T. Odean (2001): “Learning to Be Overconfident,” *The Review of Financial Studies*, 14, 1–27.

Glaser, M. and M. Weber (2007): “Overconfidence and trading volume,” *Geneva Risk Insur Rev*, 32, 1–36.

Griffin, D. and A. Tversky (1992): “The Weight of Evidence and the Determinants of Confidence,” *Cognitive Psychology*, 24, 411–435.

Grinblatt, M. and M. Keloharju (2009): “Sensation Seeking, Overconfidence, and Trading Activity,” *The Journal of Finance*, 64, 549–578.

Han, B., D. Hirshleifer, and J. Walden (2017): “Social Transmission Bias and Investor Behavior,” *Working Paper*.

Han, B. and L. Yang (2013): “Social Networks, Information Acquisition, and Asset Prices,” *Management Science*, 59, 1444–1457.

Heimer, R. Z. (2014): “Friends do let friends buy stocks actively,” *Journal of Economic Behavior and Organization*, 107, 527–540.

——— (2016): “Peer Pressure: Social interaction and the Disposition Effect,” *The Review of Financial Studies*, 29, 3177–3209.

Heimer, R. Z. and D. Simon (2013): “Facebook Finance: How Social Interaction Propagates Active Investing,” *AFA 2013 San Diego Meetings Paper*.

Hirshleifer, D. (2001): "Investor Psychology and Asset Pricing," *The Journal of Finance*, 56, 1533–1597.

Holt, C. A. and S. K. Laury (2002): "Risk Aversion and Incentive Effects," *The American Economic Review*, 92, 1644–1655.

Hong, H., J. D. Kubik, and J. C. Stein (2004): "Social Interaction and Stock-Market Participation," *Journal of Finance*, 59, 137–163.

——— (2005): "Thy neighbor's portfolio: Word-of-mouth effects in the holdings and trades of money manager," *The Journal of Finance*, 6, 2801–2824.

Ivkovic, Z. and S. Weisbenner (2007): "Information Diffusion Effects in Individual Investors' Common Stock Purchases: Covet Thy Neighbors' Investment Choices," *The Review of Financial Studies*, 20, 1327–1357.

Kahnemann, D. and A. Tversky (1972): "Subjective probability: A judgment of representativeness," *Cognitive Psychology*, 3, 430–454.

Kaustia, M. and S. Knüpfer (2012): "Peer performance and stock market entry," *Journal of Financial Economics*, 104, 321–338.

Kelly, M. and C. Ó. Gráda (2000): "Market Contagion: Evidence from the Panics of 1854 and 1857," *The American Economic Review*, 90, 1110–1124.

Kyle, A. S. and F. A. Wang (1997): "Speculation Duopoly with Agreement to Disagree: Can Overconfidence Survive the Market Test?" *The Journal of Finance*, 52, 2073–2090.

Lichtenstein, S., B. Fischhoff, and L. D. Phillips (1982): "Calibration of probabilities: The state of the art to 1980. D. Kahneman, P. Slovic, and A. Tverski (Eds.) Judgement under uncertainty: Heuristics and biases," *New York, Cambridge University Press.*

Massa, M. and A. Simonov (2005): "History vs. Geography: The role of college interaction in portfolio choice," *CEPR Discussion Paper*, 4815.

Odean, T. (1998): "Volume, Volatility, Price, and Profit When All Traders Are Above Average," *The Journal of Finance*, 53, 1887–1934.

——— (1999): "Do Investors Trade Too Much?" *The American Economic Review*, 89.

Oehler, A., M. Horn, and S. Wendt (2016): "Benefits from social trading? Empirical evidence for certificates on wikifolios," *International Review of Financial Analysis*, 46, 202–210.

Pan, W., Y. Altshuler, and A. S. Pentland (2012): "Decoding Social Influence and the Wisdom of the Crowd in Financial Trading Network," *International Conference on Privacy, Security, Risk and Trust and International Conference on Social Computing, Institute of Electrical and Electronics Engineers*, 203–209.

Park, J., P. Konana, B. Gu, A. Kumar, and R. Raghunathan (2013): "Information Valuation and Confirmation Bias in Virtual Communities: Evidence from Stock Message Boards," *Information Systems Research*, 24, 1050–1067.

Paul, P. S. and S. Lichtenstein (1971): "Comparison of Bayesian and regression approaches to the study of information processing in judgment," *Organizational behavior and human performance*, 6, 649–744.

Pirmoradi, M. and S. McKelvie (2015): "Feedback, Confidence, and False Recall in the DRMRS Procedure," *Current Psychology*, 34, 248–267.

Rabin, M. and J. L. Schrag (1999): "First Impressions Matter: A Model of Confirmatory Bias," *The Quarterly Journal of Economics*, 114, 37–82.

Roa Garcia, M. J. (2013): "Financial Education and Behavioral Finance: New Insights into the Role of Information in Financial Decision," *Journal of Economic Surveys*, 27, 297–315.

Shiller, R. J. (1984): "Stock Prices and Social Dynamics," *Brookings Papers on Economic Activity*, 2, 457–510.

——— (2010a): "Conversation, information, and herd behavior," *American Economic Review*, 85, 181–185.

Shiller, R. J. and J. Pound (1989): "Survey evidence on diffusion of interest and information among investors," *Journal of Economic Behavior and Organization*, 12, 47–66.

Shive, S. (2010): "An Epidemic Model of Investor Behavior," *Journal of Financial and Quantitative Analysis*, 45, 169–198.

Statman, M. (2014): "Behavioral finance: Finance with normal people," *Borsa Istanbul Review*, 14, 65–73.

Statman, M., S. Thorley, and K. Vorkink (2006): "Investor Overconfidence and Trading Volume," *The Review of Financial Studies*, 1, 1531–1565.

Thaler, R. H. (1999): "The End of Behavioral Finance," *Financial Analysts Journal*, 55, 12–17.

——— (2016): "Behavioral Economics: Past, Present, and Future," *American Economic Review*, 106, 1577–1600.

Tversky, A. and D. Kahnemann (1971): "Belief in the law of small numbers," *Psychological bulletin*, 76, 105–110.

——— (1974): "Judgment under uncertainty: Heuristics and biases," *Science*, 185, 1124–1131.

——— (1981): "The Framing of Decisions and the Psychology of Choice," *Science*, 211, 453–458.

Wang, G., T. Wang, B. Wang, D. Sambasivan, Z. Z. H. Zheng, and B. Y. Zhao (2015): "Crowds on Wall Street: Extracting Value from Collaborative Investing Platforms," *CSCW 2015, March 14-18, 2015, Vancouver, BC*, 17 – 30.

Weber, N. and N. Brewer (2003): "The effect of judgment type and confidence scale on confidence-accurary calibration in face recognition," *Journal of Applied Psychology*, 88, 490–499.

Wells, G. L. and A. L. Bradfield (1998): ""Good, You Identified the Suspect": Feedback to Eyewitnesses Distorts Their Reports of the Witnessing Experience," *Journal of Applied Psychology*, 83, 360–376.

| Summary: Social recognition vs. No social recognition | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Follower | No | Yes | No | Yes | No | Yes | No | Yes |
| | Investors | | Trades | | Return | | Holding | |
| All | 50,551 | 21,694 | 20.17 | 36.79 | -.000274 | -.000216 | 288.30 | 161.58 |
| Low-Return | 10,975 | 3,474 | 19.05 | 34.57 | -.001186 | -.001037 | 156.48 | 94.45 |
| Return-2 | 10,022 | 4,427 | 24.96 | 42.29 | -.000318 | -.000314 | 189.55 | 113.63 |
| Return-3 | 9,637 | 4,812 | 26.11 | 43.83 | -.000095 | -.000093 | 220.89 | 134.01 |
| Return-4 | 8,764 | 5,685 | 21.94 | 35.94 | -.000000 | -.000000 | 226.73 | 184.50 |
| High-Return | 11,153 | 3,296 | 10.46 | 22.93 | .000298 | .000239 | 613.40 | 297.45 |
| | Diversification | | Following Others | | No. Securities | | Leverage | |
| All | .32 | .44 | 34.29 | 70.85 | 5.72 | 7.11 | 87.02 | 97.19 |
| Low-Return | .13 | .17 | 15.10 | 35.01 | 4.67 | 5.80 | 95.40 | 98.47 |
| Return-2 | .24 | .29 | 23.99 | 48.58 | 5.73 | 6.77 | 93.21 | 98.34 |
| Return-3 | .39 | .45 | 37.62 | 68.70 | 6.55 | 7.53 | 91.47 | 98.34 |
| Return-4 | .66 | .74 | 86.72 | 125.37 | 8.11 | 8.52 | 92.99 | 98.09 |
| High-Return | .25 | .42 | 18.36 | 47.61 | 4.17 | 5.89 | 64.67 | 91.04 |

Table 1: Panel A: Summary statistics based on two-way sorting on social recognition and return

| | Gender | | | Age | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Female | Male | Missing | 18-24 | 25-34 | 35-44 | 45-54 | 55-64 | ≥65 | Missing |
| Total | 11,419 | 59,825 | 1,001 | 4,019 | 28,012 | 21,341 | 10,140 | 4,624 | 2,361 | 1,748 |
| Follower: Yes | 3,817 | 17,613 | 264 | 734 | 7,814 | 6,826 | 3,413 | 1,672 | 728 | 507 |
| Follower: No | 7,602 | 42,212 | 737 | 3,285 | 20,198 | 14,515 | 6,727 | 2,952 | 1,633 | 1,241 |

Table 1: Panel B: Summary statistics of demographic information

This table reports summary statistics for our data. Panel A reports summary statistics across different investor and return groups. We calculate the average of executed trades, realized returns, position holding period, level of diversification, number of investors they follow, the different instruments they invest in, and the level of leverage for each individual. We differentiate investors who receive (Follower: Yes) or do not receive (Follower: No) social recognition at any point in time. We sort investors independently into five groups based on their overall monthly average return. We require investors to trade online at for least five months over our sample period. Panel B reports an overview of the gender and age distribution of investors in our data. We report the summary statistics for the entire sample and for investors that receive (Follower: Yes) or do not receive (Follower: No) social recognition separately.

| | Model (1) | Model (2) | Model (3) | Model (4) | Model (5) |
|---|---|---|---|---|---|
| First-time follower | 29.05 | 29.80 | 31.86 | | |
| | (55.20) | (24.40) | (46.45) | | |
| Male | 2.05 | 2.51 | 2.06 | 2.51 | 2.60 |
| | (3.04) | (2.63) | (3.04) | (2.46) | (3.33) |
| Young | −11.01 | −11.01 | −7.62 | −14.53 | −10.26 |
| | (−20.60) | (−20.60) | (−10.10) | (−17.60) | (−16.53) |
| First-time follower × Male | | −0.91 | | | |
| | | (−0.68) | | | |
| First-time follower × Young | | | −6.78 | | |
| | | | (−6.38) | | |
| Second-time follower | | | | 25.14 | |
| | | | | (31.42) | |
| First-time follower and positive return | | | | | 25.04 |
| | | | | | (40.70) |
| Controls | Yes | Yes | Yes | Yes | Yes |
| Adj. $R^2$ | 0.20 | 0.20 | 0.20 | 0.19 | 0.17 |
| Observations | 39,554 | 39,554 | 39,554 | 19,866 | 24,124 |
| RMSE | 52.08 | 52.08 | 52.05 | 56.32 | 47.53 |

Table 2: Panel A: Estimation of treatment effects

| | Average treatment effect on the treated | | |
|---|---|---|---|
| | Coefficient | SE | Observations |
| First-time follower | 29.05 | .3704 | 39,554 |
| Second-time follower | 25.15 | .5646 | 19,866 |
| First-time follower and positive return | 25.04 | .4378 | 24,124 |

Table 2: Panel B: Average treatment effect on the treated

This table reports the results of the difference-in-differences estimation. We report the coefficients of average treatment effects (ATE) in Panel A and simulated average treatment effects on the treated (ATET) in Panel B together with the associated $t$-statistics and standard errors, respectively. The treatment group initially comprises all investors who receive social recognition about their investment decisions (for the first time). The control group comprises investors who do not receive social recognition. Investors in the treatment and control groups are matched with a nearest neighbor matching routine based on their gender, age range, past trading activity, realized returns, position holding periods, number of instruments used, levels of leverage, and a similar number of other investors followed prior to the treatment event. We exclude investors without a match from our analysis. Reported treatment effects are (i) the first instance of social recognition, (ii) the second instance of social recognition, and (iii) the first instance of social recognition combined with simultaneous positive market feedback. Male denotes a dummy variable taking the value one if the investor is male and zero otherwise. Young denotes a dummy variable taking the value one if the investor is 34 years or younger and zero otherwise.

| Summary: Pre and post treatment | | | | | | |
|---|---|---|---|---|---|---|
| Follower | Pre | Post | Pre | Post | Pre | Post |
| | Trades | | Return | | Holding | |
| Low Return-month | 27.04 | 22.84 | -.00073 | -.00091 | 183.62 | 214.15 |
| Return month-2 | 34.95 | 38.43 | -.00018 | -.00026 | 157.94 | 154.53 |
| Return month-3 | 37.47 | 46.50 | -.00005 | -.00007 | 132.35 | 129.60 |
| Return month-4 | 36.22 | 47.18 | .00002 | .00001 | 136.50 | 127.59 |
| High Return month | 32.68 | 36.18 | .00022 | .00021 | 166.68 | 142.57 |
| | Diversification | | No. Securities | | Leverage | |
| Low Return-month | 0.38 | 0.46 | 6.32 | 5.00 | 97.8 | 99.2 |
| Return month-2 | 0.53 | 0.57 | 8.65 | 7.38 | 97.8 | 99.3 |
| Return month-3 | 0.62 | 0.64 | 9.47 | 8.41 | 98.1 | 99.2 |
| Return month-4 | 0.61 | 0.65 | 8.97 | 7.96 | 97.2 | 99.0 |
| High Return month | 0.46 | 0.53 | 7.15 | 6.20 | 95.4 | 98.5 |

Table 3: Summary statistics based on two-way sorting on returns and pre/post-treatment periods

This table reports summary statistics for investors prior to and after experiencing social recognition (Follower). For each investor, all periods are ranked independently with respect to realized returns. We allocate all periods into five groups (low-return-month to high-return-month). We then differentiate between the month before and the month after investors receive social recognition for the first time.

| Variables | Follower | Return | Trades | Divers. | Holding | Leverage | Following |
|---|---|---|---|---|---|---|---|
| Return | 0.0287 | | | | | | |
| | (0.000) | | | | | | |
| Trades | 0.0609 | 0.0769 | | | | | |
| | (0.000) | (0.001) | | | | | |
| Diversification | 0.0737 | 0.1811 | -0.1311 | | | | |
| | (0.000) | (0.000) | (0.000) | | | | |
| Holding | 0.0285 | 0.0515 | -0.1660 | 0.1566 | | | |
| | (0.000) | (0.000) | (0.000) | (0.000) | | | |
| Leverage | 0.0052 | -0.0651 | 0.0802 | 0.0721 | -0.4380 | | |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | | |
| Following Others | -0.0228 | 0.0820 | 0.0832 | 0.2223 | -0.0479 | 0.0620 | |
| | (0.000) | (0.014) | (0.000) | (0.000) | (0.000) | (0.000) | |
| No. Securities | -0.0137 | 0.1558 | 0.3351 | 0.1051 | -0.0951 | 0.1119 | 0.561 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.011) | (0.000) |

Table 4: Correlations between selected variables

This table reports the pairwise correlations between selected variables. $p$-values are shown in parentheses. In total, our sample covers 284,058 investor-months of trading information from January 2012 to October 2015.

| | Model (1) | Model (2) | Model (3) | Model (4) | Model (5) |
|---|---|---|---|---|---|
| | Baseline | Controls | Interaction | Follower & Profit | Follower & Loss |
| Follower | 0.198 | 0.017 | 0.018 | | |
| | (29.53) | (3.89) | (4.12) | | |
| Return | | 37.87 | 32.43 | | |
| | | (8.46) | (7.13) | | |
| Trades | | 0.441 | 0.441 | 0.450 | 0.449 |
| | | (137.67) | (137.68) | (142.48) | (140.44) |
| Diversification | | 0.065 | 0.065 | 0.058 | 0.056 |
| | | (9.41) | (9.42) | (8.58) | (8.28) |
| Holding | | -0.065 | -0.064 | -0.059 | -0.059 |
| | | (-28.13) | (-27.97) | (-26.20) | (-26.11) |
| Leverage | | -0.359 | -0.359 | -0.319 | -0.323 |
| | | (-12.92) | (-12.91) | (-11.40) | (-11.53) |
| Following Others | | -0.015 | -0.015 | -0.012 | -0.012 |
| | | (-6.91) | (-6.92) | (-5.79) | (-5.75) |
| No. Securities | | 0.009 | 0.009 | 0.010 | 0.010 |
| | | (11.37) | (11.39) | (12.26) | (12.47) |
| Follower x Return | | | 71.45 | | |
| | | | (7.15) | | |
| Follower Decrease | | | | -0.132 | |
| | | | | (-13.00) | |
| Profitable | | | | 0.230 | |
| | | | | (46.39) | |
| Follower Decrease x Profitable | | | | 0.081 | |
| | | | | (5.94) | |
| Follower Increase | | | | | 0.037 |
| | | | | | (4.22) |
| Unprofitable | | | | | -0.234 |
| | | | | | (-46.89) |
| Follower Increase x Unprofitable | | | | | -0.087 |
| | | | | | (-6.51) |
| Constant | 3.523 | 2.526 | 2.524 | 2.343 | 2.583 |
| | (132.70) | (67.53) | (67.50) | (62.34) | (68.86) |
| Investor fixed effects | Yes | Yes | Yes | Yes | Yes |
| Time fixed effects | Yes | Yes | Yes | Yes | Yes |
| Observations | 284,058 | 284,058 | 284,058 | 284,058 | 284,058 |
| Adj. $R^2$ | 0.07 | 0.27 | 0.27 | 0.28 | 0.28 |
| $F$-value | 213.7 | 1027.2 | 1010.3 | 1089.1 | 1092.7 |

Table 5: Panel regression on all investors who receive social recognition

This table reports the results of our panel data regression analyses, controlling for investor and time fixed effects. The sample comprises all investors who receive social recognition and trade for at least five months using the brokerage service. The dependent variable is the log of the number of trades executed in month $t$. All independent variables are lagged by one month. We use robust standard errors clustered at the individual investor level. $t$ statistics in parentheses.

| | Model (1) | Model (2) | Model (3) | Model (4) |
|---|---|---|---|---|
| | Winner | Buy-Hold | Long Term | Frequent |
| Follower | 0.029 | 0.032 | 0.018 | 0.028 |
| | (3.89) | (4.60) | (3.87) | (5.92) |
| Return | 205.2 | 105.4 | -2.885 | 3.125 |
| | (13.80) | (9.12) | (-0.46) | (0.46) |
| Trades | 0.508 | 0.520 | 0.485 | 0.512 |
| | (73.49) | (92.80) | (118.39) | (109.53) |
| Diversification | 0.071 | 0.044 | 0.126 | 0.111 |
| | (4.66) | (3.29) | (14.58) | (11.97) |
| Holding | -0.062 | -0.069 | -0.049 | -0.055 |
| | (-13.14) | (-19.01) | (-15.40) | (-16.83) |
| Leverage | -0.211 | -0.232 | -0.232 | -0.271 |
| | (-4.49) | (-6.43) | (-4.12) | (-4.40) |
| Following Others | -0.006 | -0.006 | 0.004 | -0.001 |
| | (-1.45) | (-1.56) | (1.95) | (-0.36) |
| No. Securities | 0.003 | 0.004 | 0.006 | 0.001 |
| | (1.84) | (2.96) | (6.55) | (1.41) |
| Constant | 1.711 | 1.634 | 2.165 | 2.052 |
| | (23.15) | (28.28) | (33.61) | (29.08) |
| Investor fixed effects | Yes | Yes | Yes | Yes |
| Time fixed effects | Yes | Yes | Yes | Yes |
| Observations | 56,902 | 77,905 | 176,691 | 125,080 |
| Adj. $R^2$ | 0.322 | 0.363 | 0.300 | 0.323 |
| $F$-value | 240.4 | 410.2 | 813.0 | 623.3 |

Table 6: Regression on different investor subsamples

This table reports the results of our panel data regression analyses for different investor subsamples. Winner includes those investors who realize positive returns over the entire sample period when trading online. Buy-Hold are those investors with the highest average holing period of positions. Long term includes those investors who have traded for a long time using the brokerage service. Frequent separates those investors who execute trades with the highest frequency. We control for investor and time fixed effects. The sample comprises all investors who experience social recognition and trade for at least five months using the brokerage service. The dependent variable is the log of the number of executed trades in month $t$. All independent variables are lagged by one month. We use robust standard errors clustered at the individual investor level. $t$ statistics in parentheses.

| Summary: Returns and social recognition (investor based) | | | | | | |
|---|---|---|---|---|---|---|
| Follower | Weak | Medium | Strong | Weak | Medium | Strong |
| | Trades in t+1 | | | Follower in t | | |
| Low Return-month | 29.10 | 27.90 | 28.76 | 0.58 | 2.07 | 6.01 |
| Return month-2 | 32.55 | 32.63 | 36.95 | 0.57 | 2.06 | 6.54 |
| Return month-3 | 35.67 | 35.94 | 43.37 | 0.49 | 2.05 | 6.53 |
| Return month-4 | 36.23 | 37.75 | 46.37 | 0.61 | 2.06 | 6.21 |
| High Return month | 34.61 | 34.95 | 41.65 | 0.64 | 1.67 | 5.01 |
| | Return in t | | | Return in t+1 | | |
| Low Return-month | -.00094 | -.00094 | -.00077 | -.00018 | -.00018 | -.00016 |
| Return month-2 | -.00027 | -.00025 | -.00022 | -.00017 | -.00018 | -.00017 |
| Return month-3 | -.00005 | -.00008 | -.00007 | -.00011 | -.00012 | -.00014 |
| Return month-4 | .00001 | .00001 | .00001 | -.00009 | -.00009 | -.00012 |
| High Return month | .00023 | .00023 | .00018 | -.00017 | -.00018 | -.00020 |

Table 7: Two-way-investor-based sorting on social recognition and return

This table reports the results of our two-way sorting on return and social recognition. For each investor, all periods are ranked independently with respect to the realized returns. We allocate all periods into five groups (low-return-month to high-return-month). We independently rank months with respect to social recognition and allocate all months to three social recognition (Follower) groups (weak, medium, strong). This results in 15 return-feedback intersection months for each investor. Trades is the number of completed trades one month after receiving the two-way sorting procedure.

| Realized return distribution in each intersection month | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Return-months | Follower | p5 | p10 | p25 | Mean | p75 | p90 | p95 |
| Low-Return | Weak | -.00518 | -.00301 | -.00106 | -.00094 | -.00006 | -.00001 | -.00001 |
| Low-Return | Medium | -.00533 | -.00305 | -.00103 | -.00094 | -.00006 | -.00001 | -.00001 |
| Low-Return | Strong | -.00428 | -.00234 | -.00077 | -.00077 | -.00005 | -.00001 | -.00001 |
| Return-1 | Weak | -.00121 | -.00065 | -.00020 | -.00027 | -.00001 | .00000 | .00000 |
| Return-1 | Medium | -.00115 | -.00064 | -.00020 | -.00025 | -.00001 | .00000 | .00000 |
| Return-1 | Strong | -.00099 | -.00053 | -.00016 | -.00022 | -.00001 | .00000 | .00000 |
| Return-2 | Weak | -.00033 | -.00016 | -.00003 | -.00005 | .00000 | .00001 | .00003 |
| Return-2 | Medium | -.00040 | -.00020 | -.00004 | -.00008 | .00000 | .00001 | .00003 |
| Return-2 | Strong | -.00035 | -.00018 | -.00004 | -.00007 | .00000 | .00001 | .00003 |
| Return-3 | Weak | -.00011 | -.00003 | .00000 | .00001 | .00002 | .00008 | .00015 |
| Return-3 | Medium | -.00011 | -.00004 | .00000 | .00001 | .00002 | .00008 | .00016 |
| Return-3 | Strong | -.00013 | -.00005 | .00000 | .00001 | .00002 | .00008 | .00015 |
| High-Return | Weak | .00000 | .00000 | .00001 | .00023 | .00022 | .00066 | .00129 |
| High-Return | Medium | .00000 | .00000 | .00001 | .00023 | .00022 | .00067 | .00130 |
| High-Return | Strong | -.00002 | .00000 | .00001 | .00018 | .00017 | .00050 | .00096 |

Table 8: Return distribution in each intersection month

This table reports the return distribution of each intersection return-social recognition month in Table 7. For each investor, all periods are ranked independently with respect to the realized returns. We allocate all periods into five groups (low-return-month to high-return-month). We independently rank months with respect to social recognition and allocate all months to three social recognition (Follower) groups (weak, medium, strong).

| Summary: Returns and social recognition (monthly based) | | | | | | |
|---|---|---|---|---|---|---|
| Follower | 50% | 20% | 10% | 50% | 20% | 10% |
| | Absolute Position | | | Improved Position | | |
| | No of executed trades in the following period | | | | | |
| Low Return Investor | 37.28 | 26.91 | 20.09 | 45.51 | 26.70 | 24.12 |
| Return Investor-2 | 55.15 | 46.43 | 44.64 | 58.03 | 51.36 | 47.15 |
| Return Investor-3 | 61.60 | 68.50 | 71.53 | 60.02 | 79.05 | 94.15 |
| Return Investor-4 | 57.50 | 60.36 | 56.82 | 62.27 | 71.97 | 81.85 |
| High Return Investor | 36.19 | 36.13 | 37.78 | 42.63 | 44.55 | 46.58 |
| | Return | | | | | |
| Low Return Investor | -.00071 | -.00063 | -.00058 | -.00055 | -.00049 | -.00053 |
| Return Investor-2 | -.00006 | -.00006 | -.00005 | -.00006 | -.00005 | -.00005 |
| Return Investor-3 | -.00001 | -.00001 | .00000 | -.00001 | -.00001 | .00000 |
| Return Investor-4 | .00001 | .00001 | .00001 | .00001 | .00001 | .00001 |
| High Return Investor | .00021 | .00017 | .00014 | .00020 | .00016 | .00015 |

Table 9: Two-way monthly sorting on social recognition and return

This table reports the results of our two-way monthly sorting on return and social recognition. Each month, all investors are ranked independently with respect to the realized returns. We allocate all investors into five groups (low-return-investor to high-return-investor). We independently rank all investors with respect to their social recognition and allocate them into groups of the top 10%, top 20%, and top 50%.

| | Model (1) | Model (2) | Model (3) |
|---|---|---|---|
| (Intercept) | −18.88 | −16.29 | −16.26 |
| | (−1.18) | (−1.05) | (−1.05) |
| Return | 109.09 | 99.60 | 99.55 |
| | (1.53) | (1.43) | (1.43) |
| Risk aversion | 2.15 | 2.20 | 2.20 |
| | (2.00) | (2.10) | (2.10) |
| Male | 5.30 | 4.99 | 4.99 |
| | (1.39) | (1.34) | (1.34) |
| Age | 0.03 | −0.11 | −0.11 |
| | (0.04) | (−0.16) | (−0.16) |
| Experience | −1.68 | −1.78 | −1.78 |
| | (−1.35) | (−1.46) | (−1.46) |
| Treatment | 11.52 | | |
| | (3.34) | | |
| Follower | | 4.39 | |
| | | (3.85) | |
| AUM | | | 8.03 |
| | | | (3.85) |
| $R^2$ | 0.27 | 0.31 | 0.31 |
| Adj. $R^2$ | 0.19 | 0.23 | 0.23 |
| Num. obs. | 66 | 66 | 66 |
| RMSE | 13.48 | 13.14 | 13.14 |

Table 10: OLS regressions on investors' confidence

This table reports the results of ordinary least squares regressions on participants confidence levels in our experimental study. The dependent variable is the change in participants' confidence, measured on a 11-point Likert scale. Treatment is a dummy variable that takes a value of one if the participant is in the treatment group, zero otherwise; Follower denotes the number of observers indicated in the treatment messages; AUM indicates the Euro amount indicated in the treatment messages; Return denotes the return on investment from the previous round; Risk aversion is measured using a lottery choice procedure from Holt and Laury (2002); Male is a dummy variable that takes a value of one if the participant is male, zero otherwise; Age denotes participants' age; Experience denotes participants stock market experience. Standard errors are robust. $t$ statistics in parentheses.

## KRC Inc. (KRC)

$ 19.67 +0.33 (+1.68%)
Current price Intraday change

**Snapshot**:

| | | | |
|---|---|---|---|
| Previous Closing: | $ 19.34 | Intraday Range: | $ 19.31 - 19.69 |
| Avg. Volume: | 6,010,917 | Market Cap.: | 8.37Billion USD |
| Price Earnings Ratio: | 31.12 | Earnings Per Share: | $ 0.63 |
| Dividend yield: | 1.08 (5.58%) | 52 Week Range: | $ 17.02 - 30.70 |
| Beta: | 0.57 | Revenues: | 1.17Billion USD |
| Sector: | Financial | No. of Employees: | 551 |
| Industry: | REIT - Retail | | |

**Description:**

KRC Inc. is an independent real estate investment trust. The firm invests in the real estate markets across North America. It is primarily engaged in acquisitions, development, and management of neighborhood and community shopping centers. The firm also provides property management services relating to the management, leasing, operation, and maintenance of real estate properties. KRC Inc. was formed in 1966 and is based in New Hyde Park, New York with additional office all across North America.

Figure A1: Fundamental stock information (Page 1)

**News**:

Retail REIT, KRC Inc. announced the groundbreaking at Dania Pointe's Phase 1 retail part. Encouragingly, this project in Southern Broward County, FL, has grabbed much attention and its Phase 1 is already around 80% preleased to a number of national and regional retailers.

**1 Year Chart:**


**5 Year Chart:**


Figure A1: Fundamental stock information (Page 2)

This figure displays an example of the stock information provided to participants in their investment decisions.