The Impact of Internet Postings on Individual Investors*

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Abstract

Many people share investment ideas online. This study investigates how investment-related Internet postings influence the behavior of those who read them. We use unique data from a social trading platform that allow us to observe the trading behavior of those who post comments – the traders – as well as the trading behavior of those who potentially act on comments – the followers. There is strong evidence that comments encourage followers to replicate investment decisions of traders. However, postings do not contain value-relevant information, suggesting that personal sentiment and biases drive followers' reactions to the postings. Comments by traders who appear financially sophisticated are most influential, while followers that tend to be financially unsophisticated are most likely to trade on comments.

JEL Classification: D14, G11, G23

Keywords: Internet postings, social trading, individual investors, social interaction, textual analysis

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1 Introduction

Many individuals share investment opinions on the web.[1] While prior research examines the value of these shared ideas and documents that it varies greatly (e.g., Antweiler and Frank, 2004; Das and Chen, 2007; Chen et al., 2014; Avery et al., 2016), little is known about how investment-related Internet postings affect the investment behavior of those who read them. If investment opinions shared online contain value-relevant information, it is rational for investors to rely on these postings when making investment decisions. In contrast, if investment-related Internet postings have no predictive power for future returns, investors should not react. In this paper, we use unique data from a social trading platform to address two main questions: First, do individual investors listen to investment opinions shared online? Second, is it real information about fundamentals or personal sentiment and biases that induce investors to trade?

Social trading platforms provide an ideal setting for such an investigation. They are social networks for individual investors. On these platforms, *traders* can share their portfolios and can post comments about their shared investment strategies. In addition, *followers* can study shared portfolios and posted comments and can directly replicate investment decisions of traders in their own accounts in real time. Thus, we observe the trading behavior of those who share investment ideas as well as the trading behavior of those who follow the shared ideas. Most importantly, we observe the postings of traders that potentially influence followers.

Our data come from one of the largest social trading platforms and cover the time period from January 2013 to December 2014. The sample contains more than 2,000 shared portfolios of traders. Traders managing these portfolio post about 30,000 comments on their profile pages. In addition, replicating transactions of followers into and out of these shared trading strategies amount to about EUR 235 million (equivalent to roughly USD 310 million) over our sample period.

In the first part of the study, we analyze the determinants of Internet postings. We show

[1] On the one hand, individuals share investment ideas on investment-related online platforms such as Yahoo! Finance, Seeking Alpha, Motley Fool, and Value Investors Club. On the other hand, they also share investment ideas in classical online social networks such as Facebook and Twitter (Cogent Research, 2012).

that traders are more likely to post comments the better their recent portfolio returns are. We also examine the determinants of comment tone. To extract the tone of comments, we follow previous research and compute the fraction of positive words and the fraction of negative words in the text (e.g., Tetlock, 2007; Kothari et al., 2009; Feldman et al., 2010; Loughran and McDonald, 2011; Engelberg et al., 2012; Chen et al., 2014; Hillert et al., 2014; Huang et al., 2014; Hillert et al., 2016). We find strong evidence that good portfolio performance spurs traders' enthusiasm and significantly increases the fraction of positive words in comments. In contrast, the relation between past returns and the fraction of negative words in comments is not statistically significant. Hence, online postings are biased toward positive outcomes. This is consistent with traders being subject to the self-enhancing transmission bias, the tendency to broadcast their successes while downplaying failures (Han and Hirshleifer, 2016).

The core of our analysis is an investigation of how Internet postings affect the behavior of followers. We document robust evidence that posting comments induces followers to replicate transactions of traders. Specifically, if a trader posted a comment yesterday this increases today's net investments of followers in shared trading strategies by about 7% compared to the average daily net investments for the same portfolio. When estimating the comment-driven follower effect separately for investments and withdrawals, we find that Internet postings increase investments by more than 10%. However, they also have a positive and significant effect on withdrawals, suggesting that comments motivate some investors to walk away. We show that the comment-induced follower reaction is not only observed on the day after the posting of a comment but that the effect lasts for about three weeks. In addition, we find that a one standard deviation increase in the fraction of positive words increases net investments of followers by about 4% on average. In contrast, there is no significant relation between the negativity of comments and followers' reaction.

We run all our tests including portfolio fixed effects to control for observable and unobservable portfolio and trader characteristics that are constant over time. Thereby, any documented effect of postings on investment decisions of followers is purely driven by within-portfolio variation. Moreover, we account for potential time trends by adding day fixed effects to all our regression specifications. We also control for time-varying variables that might influence the posting of comments and at the same time investment decisions of followers such as past portfolio performance and past investment decisions of followers.

We also investigate whether our results are subject to an omitted variable problem. Rather than traders' comments genuinely influencing followers' investment decisions, it could be the case that comments and investment decisions each reflect news that traders and followers both observe directly. While day fixed effects should control for market-wide news announcements, our setting does not yet account for firm-specific news announcements. To address this concern, we rerun our analysis separately for firm-specific comments and general comments. While the former refer to specific stocks, the latter talk about traders' portfolios more broadly. We document a strong effect for general comments on followers' reaction but no effect for firm-specific comments on followers, suggesting that firm-specific news announcements are unlikely to drive our results.

We then examine why followers trade on comments posted by traders. We show that neither the posting of comments nor the tone of comments have predictive power for the future performance of traders' portfolios. Consistent with this finding, we document that a follower-weighted calendar-time portfolio formed on portfolios of traders delivers about the same performance as a calendar-time portfolio that assigns equal weights to all trader portfolios in our sample. Both portfolios tend to underperform common benchmarks. Thus, our results suggest that Internet postings do not help followers to make good investment decisions and followers' reaction to these postings is driven by personal sentiment and biases rather than by rationality. This is consistent with Shiller's (2000) idea that enthusiasm spreads from person to person and affects individual investors' decision making.

Finally, we examine how our results vary in the cross-section. First, we analyze what makes a trader particularly influential. We document that the postings of traders who have performed well recently, who have attracted new followers, and who claim to be experienced have greater influence on the trading behavior of followers. This indicates that followers tend to listen to traders that appear more financially sophisticated. However, even comments of allegedly sophisticated traders do not contain value-relevant information. Second, we examine what type of follower is most likely to listen to comments. To categorize followers, we rely on previous literature that suggests that large investors tend to be more sophisticated than small investors (e.g., Lee and Radhakrishna, 2000; Malmendier and Shanthikumar, 2007; Mikhail et al., 2007; Hvidkjaer, 2008; Barber et al., 2009; Peress and Schmidt, 2016). We find a highly significant reaction to comments for small investors but no reaction for large investors. This suggests that it is mainly unsophisticated individuals who rely on Internet postings when making investment decisions, but this does not help them to improve investment quality.

Our study contributes to several strands of research. First, our paper relates to the literature on the value of investment ideas shared on the web. These studies report mixed results. Whereas some papers document that there is a statistically and economically meaningful relation between opinions posted in online communities and future returns (e.g., Chen et al., 2014; Avery et al., 2016; Crawford et al., 2017), others find no predictive power (e.g., Tumarkin and Whitelaw, 2001; Dewally, 2003; Antweiler and Frank, 2004; Das and Chen, 2007). However, none of these existing studies observes directly how investors react to shared investment ideas. Our paper adds to this strand of research by documenting that investors rely on Internet postings, even if there is not much evidence that they contain value-relevant information.

Second, our study contributes to the literature on social interaction and investing. Using survey data, Shiller and Pound (1989) show that interpersonal communication is important for professional and individual investors' decision making. Hong et al. (2005), Cohen et al. (2008), and Pool et al. (2015) provide further evidence that fund managers' portfolio choices are influenced by word-of-mouth communication. Hong et al. (2004), Brown et al. (2008), and Kaustia and Knüpfer (2012) find that social interaction affects stock market participation of individual investors. Moreover, Ivković and Weisbenner (2007), Heimer and Simon (2012), Hvide and Östberg (2015), and Heimer (2016) provide evidence that social interaction matters for individual investors' trading behavior. However, existing research does not observe the actual communication between any two individuals or managers but typically relies on geographical proximity to infer variation in the level of interaction between investors. Thus, previous research is generally not able to determine whether correlated behavior of nearby investors is driven by investors passing along real information about fundamentals to their neighbors or by ‘irrationally exuberant’ sentiment (Hong et al., 2005). In contrast, in our setting, we can disentangle these two effects. Our results support the view that individual investors listen to each other, even though it is mainly noise and biases that are transmitted through the interactions.

Finally, our study also contributes to the literature on textual analysis in finance. A growing body of research shows that the tone in corporate disclosures, media articles, analyst reports, and Internet postings predicts future stock price changes (e.g., Tetlock, 2007; Feldman et al., 2010; Loughran and McDonald, 2011; Engelberg et al., 2012; Chen et al., 2014; Hillert et al., 2014; Huang et al., 2014). However, existing studies typically only indirectly observe investors’ reaction to the tone of the text by investigating price changes on financial markets. An exception is Hillert et al. (2016), who use textual analysis to show that mutual fund flows react to the tone of mutual fund shareholder letters. Our social trading platform also allows us to directly observe the reaction of investors to the tone of comments. However, comments posted on such a platform are fundamentally different from shareholder letters in that traders are free in the wording used in these comments, while fund managers are legally constrained to portray a fair and truthful picture of the current economic situation of a fund. Thus, we add to this literature by providing direct evidence that the trading of individual investors depends on the specific opinion revealed in the information source in a setting without any regulatory constraints.

The remainder of the paper is organized as follows. In the next section, we explain the concept of social trading in greater detail and introduce our dataset from the social trading platform. In Section 3, we first analyze what makes traders post comments. We then examine the reaction of followers to Internet postings. Next, we shed light on the predictive power of comments for the future performance of traders’ investment ideas. Finally, we analyze heterogeneity in the comment-driven follower effect. Section 4 concludes.

2 Data and variables

2.1 Social trading platforms

Social trading platforms are considered a subcategory of classical online social networks. They allow traders to share their portfolios with followers and enable them to post comments about these shared ideas. Followers can study traders' portfolios and postings and can directly replicate investment decisions of traders in their own accounts. The first social trading platforms were created in the late 2000s. As of 2016, there were several dozen platforms worldwide that offered similar services. eToro claims to be the largest one with about 5 million users. Investments of followers in shared trading strategies are estimated to amount to several billion euros across all platforms.[2]

To share their investment ideas, traders have to register with the platform. They either create a virtual portfolio on the platform or alternatively set up a real money account. Social trading platforms typically cooperate with brokerage firms. Thus, real money accounts are essentially the same as brokerage accounts. The investment universe is predefined by the platform. The majority of social trading platforms focus on equity trading and foreign exchange trading. Traders set up profile pages on the platform on which they disclose their identity and describe themselves and their investment strategy. The profile pages also show the traders' current portfolio holdings, trading history, and past portfolio performance. Moreover, one typically sees the number of followers of a portfolio. Traders can communicate with followers either by posting comments on their profile pages or by sending personal messages. Finally, platforms remunerate traders based on the number of followers they have.

Followers gather information by visiting traders' profile pages. To do so, followers typically also have to register with the platform. Moreover, to replicate investment ideas of traders, followers as well need a real money brokerage account that is linked to the platform. The replication of trading decisions usually takes place in real time. While some social trading

[2] See, e.g., "The 10 financial technology companies to watch", Financial Times, November 16, 2016; "Retail traders wield social media for investing fame", The Wall Street Journal, April 21, 2015; "Social trading takes off for the masses", The Financial Times, November 5, 2014; "UK's financial regulator warns on copy trading", The Financial Times, March 10, 2014; "Social trading targets savvy retail investors", The Financial Times, June 22, 2013.

platforms allow investors to copy single transactions of traders, the predominant form of social trading is the replication of entire investment strategies. The basis for actual returns received by followers is the returns after transaction costs and fees charged by the platform and the partnering brokerage houses.

Our data come from a leading European social trading platform. The investigation period starts in January 2013 and ends in December 2014. We have information on all portfolios of traders that followers can replicate in their own accounts. This results in a sample of 2,161 portfolios managed by 1,314 traders and 475,288 portfolio-day observations. As of December 2014, 2,022 portfolios are still alive and 139 portfolios are defunct. In January 2013, our sample starts with 220 portfolios. Thus, the platform has experienced strong growth over our investigation period. The amount of money invested by followers increases from EUR 6.2 million in January 2013 to EUR 52.9 million in December 2014. Panels A and B of Figure 1 graphically illustrate the growth in the number of portfolios as well as the growth in follower funds over our sample period.

2.2 Comment characteristics

On our platform, traders can communicate with followers by posting comments on their profile pages. This platform does not allow users to send each other personal messages. The only way for followers to gather information about a portfolio is to visit the trader's profile page, where the postings are just one click away. We know from our social trading platform that about one-third of all profile page visitors click on traders' comments, another third of visitors click on the current portfolio holdings of traders, and the remaining third click on other parts of profile pages. To understand the nature of the posted comments, it is helpful to look at examples. Comments are either firm-specific or general. Figure 2 provides six fairly typical examples of comments published on the platform, of which three are firm-specific comments and the other three are general comments. Some of the posts are backward looking providing an explanation for the past performance of the portfolio. Others are forward looking containing a predicted price change and some explanations for the prediction. Traders also discuss the general economic environment in their comments. Sometimes comments are also used to advertise trading strategies. We drop 5,317 comments that contain fewer than five words as these comments tend not to be informative.[3] This leaves us with a sample of 29,204 comments.

Our main independent variables of interest capture different aspects of the postings of traders. We create an indicator variable that equals one on days on which traders post at least one comment on their profile page, and zero otherwise. We also count the number of comments posted on days on which traders communicate. To measure the overall length of comments, we compute the number of words per comment. When there are multiple comments on a day, we calculate the average number of words across comments. To extract traders' opinions from comments, we build on prior research, which suggests that the frequency of positive words and the frequency of negative words used in a text measures the tone of the text (e.g., Tetlock, 2007; Kothari et al., 2009; Feldman et al., 2010; Loughran and McDonald, 2011; Engelberg et al., 2012; Chen et al., 2014; Hillert et al., 2014; Huang et al., 2014; Hillert et al., 2016). As most of our comments are not in English, we cannot employ the widely used Loughran and McDonald (2011) word lists that were specifically designed for financial matters.[4] Instead, we rely on positive and negative word lists based on the Harvard IV-4 dictionary (Remus et al., 2010). These word lists were developed to measure positive and negative emotions in a general context. However, the Harvard IV-4 dictionary has also been applied in a finance context in previous research (e.g., Tetlock, 2007; Kothari et al., 2009; Feldman et al., 2010; Engelberg et al., 2012; Hillert et al., 2016). The two word lists comprise 1,818 positive words and 1,650 negative words. Table A1 in Appendix B reports the 25 positive words and the 25 negative words that appear most frequently in traders' posts. The five most commonly used positive words are 'gain', 'up-to-date', 'good', 'new', and 'value'. The most frequently used negative words are 'unfortunately', 'tight', 'end', 'loss', and 'small'. In the sample comments provided in Figure 2, we underline words that are included in our dictionary. The tone measure is then constructed as the sum of the number of positive (negative) words in a comment divided by

[3]When replicating our analyses including all comments, we obtain results that are largely unchanged.

[4]The Loughran and McDonald (2011) dictionary is constructed based on textual analysis of 10-K filings. Traders on our platform certainly use a different wording than that used in 10-K filings. Thus, it is not entirely clear whether the word lists of Loughran and McDonald (2011) would be suitable in our setting.

the sum of the total number of words in the comment. When a trader posts more than one comment per day, we compute the average tone across comments.

Panel A of Table 1 provides descriptive statistics on our posting metrics. Traders post comments on 4.0% of all days. For 1,077 portfolios, we observe at least one comment during our investigation period, while traders managing the remaining 1,084 portfolios do not post comments at all. On those days on which traders communicate, they post on average 1.5 comments. Explanations provided in comments tend to be rather short. The average (median) length of a comment is 39 (22) words. This is consistent with Anweiler and Frank (2004) who report that the number of words in messages posted on Yahoo! Finance and Raging Bull is typically between 20 and 50. The average fraction of positive and negative words used in comments is 4.9% and 1.6%, respectively. The percentage of negative words is consistent with Chen et al. (2014). Using the dictionary of Loughran and McDonald (2011), they report that the average fraction of negative words in comments posted on Seeking Alpha is 1.8%.[5] The fact that the percentage of positive words is much higher than the percentage of negative words provides first suggestive evidence that the postings of traders are biased toward positive outcomes.

2.3 Follower characteristics

Our platform enables followers to link their real money brokerage accounts to the platform. Once an investor decides to follow a trader, the trader's investment decisions are proportionately replicated in the follower's portfolio. In total, our sample includes 43,676 transactions executed by followers into and out of trading strategies, of which 28,742 are investments and 14,932 are withdrawals.

Our main dependent variable captures the transactions of followers. On each day, we compute the net investments of followers in shared investment ideas of traders.[6] To make our data more normally distributed, we follow previous research and make use of the inverse

[5] Chen et al. (2014) do not report the fraction of positive words in comments.

[6] The mutual fund literature typically computes net flows as the percentage growth of a fund. This is not a suitable measure in our setting as most portfolios in our sample are created during our investigation period and thus they either do not have any followers at all or only very few followers. In these cases, percentage growth is either not defined or inflated.

hyperbolic sine transformation (e.g., Burbidge et al., 1988; Kale et al., 2009; Karlan et al., 2016). Taking the inverse hyperbolic sine is an alternative to a log-transformation when a variable takes on zero or negative values.[7]

Panel B of Table 1 presents descriptive statistics on transactions of followers. The average (median) trade size is EUR 5,360 (EUR 2,237). With an average trade size of EUR 6,124 withdrawals tend to be larger than investments (EUR 4,961). The size of transactions of followers suggests that social trading platforms mainly attract retail investors. Barber et al. (2009) argue that trades that are smaller than USD 5,000 are individual investor trades. There are a handful of very large investments of up to EUR 300,000, indicating that there are a few institutional players or very wealthy individuals that replicate the shared investment strategies. Overall, transactions of followers into and out of shared portfolios amount to more than EUR 234 million over our investigation period. Daily net investments of followers are positive on average and amount to EUR 107. This is not surprising given the strong growth of the platform over our sample period. On average, followers invest EUR 292 per day and they withdraw EUR 185 per day.

2.4 Performance characteristics

To measure the performance of traders' portfolios, we compute daily raw returns and daily alphas. We determine the portfolio performance net of bid-ask spreads and fees. As traders invest 91% of their non-cash portfolio holdings in equities, we employ a standard equity asset pricing model to determine abnormal returns of portfolios. The model contains an equity market factor as well as the investment style factors of Fama and French (1993) and Carhart (1997). We construct factors using MSCI indices as these indices are investible for retail traders. Since two-thirds of the stock holdings in portfolios are invested in European stocks, we use European MSCI indices. We employ the MSCI Europe Index as proxy for the market. The size factor (SMB) is approximated by the difference in daily returns between the MSCI Europe Small Cap Index and the MSCI Europe Index. The value factor (HML) is

[7] Alternatively, we could transform all observations by adding a constant equal to the absolute value of the minimum net investment to each observation. For this transformation, our results are qualitatively similar to the reported results.

approximated by the return difference between the MSCI Europe Value Index and the MSCI Europe Growth Index. Moreover, we use the MSCI Europe Momentum Index as a proxy for the momentum factor. The risk-free rate is captured by daily returns on the J.P. Morgan 3 Month Euro Cash Index. Data on indices are obtained from Thomson Reuters Datastream. To determine daily alphas of portfolios, we estimate factor exposures over 6-month rolling windows from t-126 to t-1. Alphas are then calculated as the difference between daily raw returns of portfolios and returns predicted by the estimated factor loadings.[8]

Panel C of Table 1 provides information on the distribution of returns and alphas in our sample. The average (median) annualized return of portfolios amounts to -1.7% (-0.7%). Moreover, the average (median) alpha is -5.8% p.a. (-2.0% p.a.). Thus, portfolios in our sample tend to underperform common benchmarks.[9]

2.5 Portfolio and trader characteristics

Our dataset also includes information on various portfolio and trader characteristics. In Panel D of Table 1, we present summary statistics on portfolio characteristics. To determine the number of followers of a portfolio, we count the number of follower transactions over time. Similarly, to compute the amount of money followers have allocated to a portfolio of a trader, we sum up net investments over time. The average portfolio in our sample is followed by eight individuals who have invested EUR 33,536. However, there is substantial variation in the number of followers and in funds of followers across different portfolios. The median portfolio has no followers, while the most popular portfolio in terms of number of followers has more than 1,400 followers and followers have allocated over EUR 8 million to the most popular portfolio in terms of follower funds. We define the age of a portfolio as the number of calendar days since the creation of the portfolio on the platform. On average, portfolios are 263 days old in our sample. Moreover, we create a dummy variable that equals one for

[8] In our stability tests, we rerun our analysis using alphas from a simple CAPM and alphas from a six-factor model that additionally includes a call option and a put option factor to account for the non-linear payoff profiles that result from the traders' use of derivative instruments. The two option factors are constructed as in Agarwal and Naik (2004) using at-the-money European call and put options on the Euro Stoxx 50. We obtain similar results with these alternative factor models.

[9] The average annualized gross return (alpha) of portfolios is 0.5% (-3.8%), indicating that bid-ask spreads and fees amount to about 2% p.a.

traders who have their own money invested in their trading strategy, and zero otherwise. The platform requires traders to allocate several thousand euros to their portfolios to be flagged as real money accounts. According to this classification, about 13% of all portfolios in our sample are classified as real money portfolios and the remaining portfolios are virtual portfolios.

On our platform, the investment universe that traders can pick securities from consists of stocks, funds, and derivatives. The average portfolio contains 12 different securities. More than half of the average portfolio is invested in stocks, of which approximately two-thirds are held in European stocks and one-third in non-European stocks. About one-fifth of the mean portfolio is held in mutual funds and exchange-traded funds, of which about 70% are equity funds. Only about 1% of portfolio holdings are allocated to derivative instruments. Moreover, traders hold a substantial fraction of 20.8% of their portfolios in cash.[10] The remaining 2.5% of the average portfolio are held in securities we cannot identify. On average, traders place about one trade per day. Daily turnover is defined as the average of the value of all purchases and the value of all sales executed on a specific day divided by the value of the trader's portfolio at the beginning of the day. The mean daily turnover is 2.7%. Hence, traders turn over their portfolios about seven times per year on average, implying that they tend to trade excessively. For comparison, in the discount brokerage dataset of Barber and Odean (2000), the average household turns over 75% of its portfolio annually. However, it is not surprising that traders on this social trading platform trade more actively given that the only transaction costs the platform imposes are bid-ask spreads.[11] Moreover, most of these traders do not have their own money at stake. As the distribution of these variables is heavily skewed, we winsorize the number of trades and the turnover at the 99% level to eliminate the effect of outliers.

Finally, Panel E of Table 1 summarizes the characteristics of traders. Only 1.2% of all portfolios are managed by professional money managers. The platform verifies whether these

[10] Traders are generally not able to use leverage. However, the deduction of fees from traders' accounts might result in negative cash positions.

[11] In the dataset of Barber and Odean (2000), commissions amount to 2.1% for purchases and 3.1% for sales and thus they are substantially higher than bid-ask spreads, which are 0.3% for purchases and 0.7% for sales. Our platform does not charge any commissions.

traders are indeed professional money management firms. Thus, users sharing investment ideas in this online community are mainly individual investors. When setting up their profile page, traders indicate their years of trading experience. Close to 95% of portfolios are administered by traders who claim to have more than three years of trading experience. Furthermore, only 2.7% of all portfolios are managed by a woman. Finally, traders handle about 2.5 portfolios on average over our investigation period. Appendix A provides detailed descriptions of all variables used throughout the study.

3 Empirical analysis

Our unique dataset allows us to perform four sets of novel tests: First, we analyze the determinants of Internet postings (Section 3.1). Second, we test whether comments posted on traders' profile pages encourage followers to replicate traders' investment strategies (Section 3.2). We go on to examine why followers listen to the posts of traders (Section 3.3). Finally, we investigate how our findings differ across traders and followers (Section 3.4).

3.1 Determinants of comments

We begin our empirical investigation by looking at what makes traders post comments and what determines the tone of comments. To do so, we conduct multivariate analyses and use the different comment characteristics as dependent variables and relate them to performance, follower, portfolio, and trader characteristics. All time-varying explanatory variables are lagged by one day to address potential reverse causality concerns. Moreover, we include day fixed effects in all regressions to control for the overall market environment. Standard errors are clustered at the portfolio level.

Results are presented in Table 2. In Column 1, the dependent variable is the indicator variable that is equal to one on days on which traders post at least one comment, and zero otherwise. Thus, we run a logit regression and report marginal effects. The coefficient on yesterday's return is positive and highly statistically significant (t-statistic of 7.59), implying that traders are more likely to post comments when their portfolios performed well. The magnitude of the coefficient suggests that a one standard deviation increase in yesterday's return increases the probability of observing a comment today by 4.6%. We also find a positive impact of investments of followers on the likelihood of observing a comment. The positive and significant coefficient on the total amount of money invested by followers indicates that traders managing more popular strategies tend to post more comments. The time since inception is significantly negatively correlated with the comment dummy. This implies that traders are more likely to post after they have set up a portfolio and the communication frequency decreases over time. Moreover, the positive and significant coefficient on the real money account dummy indicates that traders who have their own money at stake tend to communicate more actively. The number of securities in a portfolio is positively correlated with the comment dummy. This is intuitive as a diverse portfolio means that there is a lot to write about. Finally, we document that traders who trade more frequently are more active communicators. This is most likely driven by active traders spending more time on the platform and traders commenting on executed transactions.

In Column 2, we focus on days on which traders post at least one comment and use the logarithm of the number of comments per day as the dependent variable. Thus, we run an OLS regression rather than a logit regression. The coefficients on past short-term performance and recent net investments of followers are again positive and statistically significant at the 1% level. Hence, past performance and past investments of followers not only affect whether traders post comments but they also impact the number of posts on days with at least one comment. Consistent with our findings in Column 1, the coefficient on age is negative and significant, the coefficient on the number of securities in a portfolio is positive and significant, and the coefficient on turnover is positive and significant. We also find evidence that professional traders and female traders post fewer comments.

In Column 3, we investigate what determines the length of comments. To do so, we use the logarithm of the number of words per comment as our dependent variable and regress it on our standard set of independent variables. The coefficient on yesterday's return is negative and significant, suggesting that comments are shorter after more positive outcomes and traders provide more extensive explanations after more negative outcomes. Moreover, traders of more popular strategies in terms of followers and female traders post significantly longer comments.

In Columns 4 and 5, we use the fraction of positive words and the fraction of negative words in comments as dependent variables, respectively. We again focus on days on which traders post at least one comment. In Column 4, the past portfolio performance has a strongly positive effect on the fraction of positive words in comments. Thus, if portfolios perform well, traders tend to be enthusiastic about their investment ideas and share their enthusiasm with followers. A one standard deviation increase in yesterday's return increases the fraction of positive words in a comment by 3.6% on average. In contrast, when focusing on the fraction of negative words in Column 5, we find no significant relation between past returns and negativity. This again provides evidence that traders are more reluctant to talk about failure than to talk about success. Looking at the other explanatory variables in Columns 4 and 5 that display a significant relation with comment tone, we find that traders of less popular trading strategies, professional traders, and traders who manage fewer portfolios communicate more enthusiastically. Moreover, traders who do not have their own money at stake, traders who trade excessively, professionals, and male traders tend to use more negative words in their posts.

In summary, we find strong evidence that the communication of traders is biased toward positive outcomes. The platform's remuneration scheme incentivizes traders to appear successful as traders are remunerated based on the number of followers they have. While not every online community rewards its users financially for sharing investment ideas and attracting followers, reputational concerns are likely to have a similar effect on the posting behavior of traders. Han and Hirshleifer (2016) refer to the tendency of investors to recount to others their investment victories more than their defeats as the self-enhancing transmission bias.

3.2 Comments and transactions of followers

Next, we analyze whether followers base their investment decisions on postings or whether they ignore traders' communication. The only way followers can gather information about a portfolio of a trader is by visiting the trader's profile page, where they can then click on the trader's comments. We know from our social trading platform that about one-third of all profile page visitors click on traders' comments. Thus, it is highly likely that followers frequently read the comments posted by traders. To analyze whether comments affect followers' investment behavior, we run panel regressions and regress today's net investments of followers in a shared trading strategy on a dummy variable that equals one if a trader posted a comment yesterday, and zero otherwise. Specifically, we use the inverse hyperbolic sine of daily net investments of followers as dependent variable. To control for the impact of past portfolio performance on investment decisions of followers, we include the portfolio return on each of the past five trading days, the portfolio return over the past month, the past three months, the past six months, the past year, and the portfolio return since inception as control variables.[12] To control for potential effects of past investment decisions of followers on future investment decisions, we add the net investments of followers over the past five trading days and the logarithm of follower funds as controls. Furthermore, we include the logarithm of age, the dummy that equals one if the trader has own money at stake, the number of securities held in the portfolio, the portfolio turnover, the dummy that equals one for professional money managers, the dummy that equals one for experienced traders, traders' gender, and the number of portfolios managed by the trader as additional control variables. We do not report coefficient estimates of control variables for space reasons. In our most robust specification, we additionally include different fixed effects. We include portfolio fixed effects to account for all portfolio and trader characteristics that remain constant over time. This is equivalent to examining the impact of comment posting on followers' investment decisions in a within-portfolio setting. To control for the overall performance of the market as well as time trends in communication, we include day fixed effects. Standard errors are clustered at the portfolio level.

Results are reported in Table 3. In Column 1, we run the regression without control variables. In Column 2, we add the full set of control variables. In Column 3, we additionally include portfolio and day fixed effects. If Internet postings attract followers, then the coeffi-

[12] Results do not change materially if we use past portfolio alphas instead of past portfolio returns.

cient on the comment dummy should be positive. If Internet postings motivate followers to leave, we expect the coefficient estimate to be negative. We find that posting a comment has a positive effect on followers' allocation of funds to the respective trading idea. The effect is statistically significant at least at the 5% level. In the most robust specification in Column 3, we find that the posting of comments on the preceding day increases net investments of followers by 6.7% compared to the average daily net investments for the same portfolio. This is also economically meaningful. Thus, there is strong evidence that the soft information transmitted through comments posted on traders' profile pages matters for investment decisions of followers.

Thus far, we have focused on *net* investments of followers. The documented effect of comments on net investments could be driven by comments attracting new followers or by traders' being able to prevent followers from withdrawing money. To disentangle these two mechanisms, we re-estimate our baseline specification from Column 3 of Table 3 separately for purchases and sales of followers.

Results are presented in Table 4. In Column 1, we find that Internet postings have a positive and highly statistically significant effect on investments of followers (t-statistic of 5.19). Interestingly, we also document a positive relationship between postings and withdrawals in Column 2, suggesting that comments not only attract new followers but also motivate some followers to walk away. The net effect is positive as posting a comment increases investments by 12.4%, while it increases withdrawals by 4.1% only.

Next, we examine how the posts of traders affect the investment behavior of followers in the longer run. Comments remain on the profile pages of traders after they were published.[13] Thus, it might well be that they do not only attract followers immediately after they were published but also in the longer run. Alternatively, it could be the case that the comment-driven follower effect reverses after some time. To shed light on the longer-term effects of traders' postings, we turn to a longer-term analysis over several weeks. Specifically, for the

[13]While traders on this platform cannot alter posted comments, they can delete comments from their profile pages. To investigate whether traders frequently drop comments, we randomly select 50 portfolios and collect posted comments at two points in time with a gap of approximately six months. We do not find a single trader that has deleted comments from the profile page. Thus, deletion of selected comments ex post should not be a concern in our analysis.

two months after the posting of a comment, we compute average daily net investments of followers for each week and rerun our main regression from Column 3 of Table 3.

Regression estimates are reported in Table 5. Results in Columns 1 to 3 show a significant impact of comments on the trading behavior of followers within the first three weeks after the posting of a comment. Daily net investments are 16.8% higher in week 1, 8.9% higher in week 2, and 9.6% higher in week 3 relative to the average daily net investments for the same portfolio. The effects are statistically significant at least at the 5% level. After week 3, we find insignificant coefficient estimates. In weeks 7 and 8, the coefficient estimates on the comment dummy turn from positive to negative but they still lack statistical significance. Thus, there are only some weak signs of a reversal over the longer run, suggesting that the follower reaction is relatively persistent.

To dig deeper, we investigate the impact of other comment characteristics on investor behavior. Rather than regressing daily net investment of followers on the lagged comment dummy, we focus on days with at least one comment published on the preceding day and use the logarithm of the number of comments, the logarithm of the length of comments, and comment tone as main explanatory variables. We again include the full set of control variables as well as portfolio and time fixed effects in all our regressions.

Results are presented in Table 6. In Column 1, we test whether the posting frequency on days with at least one comment matters for followers' investment behavior. The positive coefficient estimate on the number of comments suggests that the more traders write, the more followers they attract. However, the effect is not statistically significant at conventional levels (t-statistic of 1.12).

We then analyze whether the length of comments affects the reaction of followers. Thus, in Column 2, the logarithm of the number of words per comment serves as our main independent variable. The coefficient estimate on this variable is also positive, indicating that followers react stronger to longer comments. However, this result is again not statistically significant (t-statistic of 0.51).

In Columns 3 and 4 of Table 6, we investigate the role of comment tone. We again focus on days with at least one comment posted on the preceding day. We find that the coefficient estimate on the fraction of positive words is positive and statistically significant (t-statistic of 1.91), suggesting that followers are more willing to replicate a trading strategy the more positively a comment is written. A one standard deviation increase in the fraction of positive words leads to net investments of followers that are 3.9% higher on the following day. In contrast, the relation between negativity and net investments of followers is not statistically different from zero (t-statistic of 0.89).

Finally, in Column 5, we include all comment characteristics simultaneously. This yields inferences that are qualitatively similar. We still document a positive and significant effect of traders' enthusiasm on followers' net investments (t-statistic of 1.84).

Next, we assess whether our results are subject to an omitted variable problem. It could be the case that traders post comments following firm-specific news announcements and followers might know the securities traders hold in their portfolios. Therefore, followers' reaction to the posting of comments could be a reaction to corporate news announcements rather than a reaction to the posting of comments. This appears rather implausible as traders hold on average 12 securities in their portfolios and frequently change the portfolio composition. It is therefore rather unlikely that followers are always up-to-date about the portfolio constituents. Moreover, followers cannot search trading strategies for specific securities. However, to address this concern, we make use of an additional feature of our data. When posting a comment, traders have to classify comments as either firm-specific or general comments. Figure 2 provides examples of both types of comments. While the firm-specific comments might be affected by corporate news announcements, general comments tend to talk about portfolios more broadly. In our sample, 52.0% of all comments are firm-specific comments and the remaining 48.0% are general comments. We re-estimate the regression form Column 3 of Table 3 and all the regressions from Table 6 separately for firm-specific comments and general comments.

Results of this robustness test are presented in Table A2 in Appendix B. When focusing on firm-specific comments in Columns 1 to 6, none of our comment characteristics shows a statistically significant relation with the investment behavior of followers. However, in Columns 7 to 12, the coefficient on the comment dummy and the coefficient on the percentage of positive words are positive and statistically significant, which is consistent with our results in Tables 3 and 6. This suggests that our findings are not driven by firm-specific news announcements that direct investors' attention toward certain portfolios but rather by the comments themselves.

In summary, we provide strong evidence that investment-related comments posted in an online community encourage trading by followers. There is not only an immediate comment-driven follower reaction but the effect lasts for several weeks.

3.3 The predictive power of comments for future performance

In this section, we investigate why investors listen to the comments of traders. The comment-driven follower effect could be rational if comments contain value-relevant information and help followers to identify portfolios that deliver superior performance. Alternatively, if comments are not informative, followers seem to be fooled by personal sentiment and biases transmitted through comments. To differentiate between these two alternative explanations, we test whether comments posted by traders have predictive power for the future performance of portfolios. To do so, we regress daily portfolio returns and daily portfolio alphas from our four-factor model on our five communication metrics. Comment characteristics are lagged by one trading day. The same set of control variables as in Table 3 is included in every regression but not reported. We again also include portfolio fixed effects and day fixed effects in all specifications. As before, standard errors are clustered at the portfolio level.

Results are presented in Table 7. In Columns 1, 3, 5, 7, 9, and 11, we use daily portfolio returns as dependent variable and in Columns 2, 4, 6, 8, 10, and 12 daily portfolio alphas. Coefficient estimates for the impact of comments on future performance are all insignificant except for Columns 7 and 11. In Columns 7 and 11, the coefficient on the fraction of positive words is positive and statistically significant, suggesting that portfolios indeed deliver superior raw returns after the posting of more positive comments. However, when looking at the more meaningful results based on the four-factor model in Columns 8 and 12, the coefficient on positivity turns insignificant. This implies that comments contain little predictive value and points toward personal sentiment and biases as the driving force behind followers' reactions.

We assess the robustness of our results by looking at a longer investment horizon. We use 1-month cumulative raw returns and 1-month cumulative abnormal returns (CARs) as performance measures rather than 1-day returns and 1-day alphas and re-estimate the specifications from Table 7.

Results of this stability test are reported in Table A3 in Appendix B. We find that comment characteristics also do not have much predictive power for the 1-month performance of portfolios. The only coefficient estimates that are statically significant are the ones on the fraction of positive words when focusing on raw returns (Columns 7 and 11). However, once we turn to the more meaningful abnormal returns, all coefficient estimates turn statistically insignificant.

If followers base their investment decisions on traders' comments and comments do not contain value-relevant information, we expect a follower-weighted portfolio of trading strategies to deliver about the same performance as a portfolio that weights trader portfolios equally. To test this conjecture, we form one value-weighted calendar-time portfolio in which we weight trader portfolios according to the capital that follows the strategies and one equal-weighted calendar-time portfolio in which we assign equals weights to all strategies in our sample. The latter portfolio captures the performance followers would have generated if they had not actively selected portfolios of traders. This yields two time series of daily raw returns from January 2013 to December 2014. To determine alphas of the two portfolios we again employ our four-factor model.

Table 8 reports alphas and factor loadings of the two portfolios. In Column 1, we present results for the follower-weighted portfolio. The annualized alpha of this portfolio amounts to about -6.7%, but it is not statistically significant at conventional levels (t-statistic of 1.34). In Column 2, the alpha of the equal-weighted portfolio is about -7.5% p.a. (significant at the 5% level). Hence, both portfolios tend to underperform common benchmarks. Most importantly, in Column 3, we present results for the difference portfolio and document that the difference in alphas between the two portfolios amounts to 0.8% p.a. and is not statistically significant (t-statistic of 0.25). Thus, there is not much evidence for selection abilities of followers, which is consistent with followers listening to traders' comments and comments not containing value-relevant information. With respect to the factor loadings, we find that both portfolios load positively on the market factor and the investment style factors of Fama and French (1993) and Carhart (1997). The results in Column 3 suggest that followers load more heavily on small stocks compared to traders.

Taken together, the findings in this section show that Internet postings influence the investment behavior of followers despite the fact that they do not reflect information sharing. Hence, these results support Shiller's (2000) view that personal sentiment and biases spread from person to person and affect investment decision making. As a consequence, followers perform as poorly as the average trader on this platform.

3.4 Which traders and followers drive results?

Next, we examine heterogeneity in the comment-driven follower effect. Our results thus far show that the traders' postings play an important role for followers' investment decisions on average. However, there are probably some traders that are more influential than others. We hypothesize that comments are more influential if traders appear more financially sophisticated. To examine cross-sectional differences in our results, we re-estimate our baseline regression from Column 3 of Table 3 and interact the comment dummy variable with all portfolio and trader characteristics.

Results of this analysis are presented in Column 1 of Table 9. The positive and significant coefficient estimate on the interaction term between the comment dummy and the past return suggests that comments attract more followers when the underlying portfolio has performed well recently. This provides support for our conjecture that comments of traders who appear to be successful are more influential. Comments are also more influential when traders have attracted new followers in the recent past as indicated by the positive coefficient estimate on the interaction term between the comment dummy and the past net investments. This suggests that investors also consider the size of a trader's online following as a proxy for quality. Furthermore, we find that followers are more likely to trade on posts of traders who have set up their portfolios only recently. In addition, followers tend to listen to comments of traders who display a high level of trading activity. Moreover, posts of traders who claim to be experienced attract significantly more followers than posts of traders who report to be unexperienced. This is again consistent with the view that followers prefer posts of (allegedly) sophisticated traders. Finally, the coefficient estimate on the interaction term between the comment dummy and the professional money manager dummy is positive, suggesting that followers are also more likely to listen to comments of professionals. However, this effect is not statistically significant at conventional levels (t-statistic of 0.80).

In Columns 2 and 3 of Table 9, we analyze whether more influential postings are also more informative. In the previous section, we document that comments do not have predictive power for future returns and alphas on average. However, it could be the case that some comments are informative even though the average comment is not. We re-estimate the regressions from Columns 1 and 2 of Table 7 and interact the comment dummy with all portfolio and trader characteristics. In Column 2 of Table 9, the dependent variable is the daily portfolio return and in Column 3 the daily portfolio alpha. The only coefficient estimate that is statistically significant across both specifications is the one on the interaction term between the comment dummy and the experienced trader dummy. The coefficient estimate is negative, suggesting that portfolios of traders who claim to be experienced significantly underperform other portfolios after comment posting. Even though it appears rather implausible, this result could be driven by experienced traders correctly predicting negative future portfolio performance in their comments. Thus, in unreported tests, we investigate whether the interaction term between the fraction of negative words in comments and the experienced trader dummy has any predictive power for future portfolio performance. However, this does not seem to be the case, suggesting that (allegedly) experienced traders do not deliberately underperform other traders after the posting of comments.

Next, we investigate which investors are most responsive to Internet postings. We hypothesize that our findings are mainly driven by unsophisticated individuals as comments tend not to be informative. As we do not observe any follower characteristics directly, we use trade size to categorize followers. Previous research shows that large trades tend to be executed by (more sophisticated) professional investors, while small trades tend to be carried out by (rather unsophisticated) individual investors (e.g., Lee and Radhakrishna, 2000; Malmendier and Shanthikumar, 2007; Mikhail et al., 2007; Hvidkjaer, 2008; Barber et al., 2009; Peress and Schmidt, 2016). In our descriptive statistics, we report the average (median) trade size in our sample to be EUR 5,360 (EUR 2,237). Thus, we use EUR 5,000 (EUR 2,500) as cutoff point and classify transactions that are below or equal to this threshold as small trades and transactions above this threshold as large trades. To investigate whether results differ across followers, we rerun our baseline specification from Column 3 of Table 3 separately for small and large trades.

Results of this analysis are reported in Table 10. In Columns 1 and 2 (Columns 3 and 4), we present coefficient estimates from the regressions using EUR 5,000 (EUR 2,500) as cutoff point. The small trades we focus on in Column 1 only account for about one quarter of the overall transaction volume of followers. Nevertheless, we find a strong comment-driven follower effect. In contrast, when focusing on large trades in Column 2, the coefficient estimate on the comment dummy is neither statistically nor economically meaningful. This suggests that our findings are indeed driven by small investors. In Column 3, when using EUR 2,500 as cutoff point, small trades constitute only 11.7% of the total transaction volume but the coefficient estimate on the comment dummy variable is still about twice as large as the coefficient estimate on the comment dummy in Column 4, where we restrict our sample to large trades. Consistently, the comment-driven follower effect in Column 3 is highly statistically significant (t-statistic of 2.81), while the comment-follower relation is not statistically significant at conventional levels in Column 4 (t-statistic of 1.01). Thus, our results are robust to variations in cutoffs.

In summary, we find that comments of traders who appear to be financially sophisticated are more influential than comments of traders who appear to be less skilled. However, even these influential comments do not contain value-relevant information. Moreover, we show that the comment-driven follower effect is mainly driven by small investors that are often considered to be unsophisticated market participants. This is consistent with our findings in the previous sections that followers listen to comments even though they do not predict future performance.

4 Conclusion

This paper investigates the role of Internet postings on investment decisions of individuals. We first document that traders with good short-term portfolio performance are more likely to post comments on their profile pages and their postings contain a higher fraction of positive words. Even though comments are biased toward positive outcomes, we find strong evidence that the posting of comments and the positivity of comments impact investment decisions of followers. We then show that comments do not have predictive power for the future performance of shared trading strategies. Hence, Internet postings do not seem to trigger a rational reaction but it is rather personal sentiment and biases that are transmitted through these comments. This supports Shiller's (2000) view that enthusiasm spreads from person to person and affects individuals' investment behavior. In a cross-sectional analysis, we find that comments of traders who appear sophisticated attract more followers, but even these comments do not help to predict future portfolio performance. Moreover, we show that our results are mainly driven by small investors that are typically considered to be unsophisticated. Overall, this paper suggests that it is primarily unsophisticated individuals that rely on the recommendations of others shared on the web when making investment decisions, but there is not much evidence that online interactions help these unsophisticated market participants to improve their investment quality.

While investigating the reaction of individual investors to Internet postings by looking at a social trading platform has several advantages, the main limitation of our study is that all information we use comes from one platform only. Therefore, it is a valid question whether the platform and its users are representative. However, the setup of investment-related online communities is relatively similar across different providers. In particular, all of them are characterized by low barriers to entry, thereby attracting uninformed traders and followers. Moreover, even if not every platform remunerates its traders financially for sharing investment ideas and attracting followers, reputational concerns are likely to have a similar effect on the posting behavior of traders. Therefore, we see no obvious reason that would make us believe that traders and followers on our platform are different from traders and followers on other platforms in any fundamental way.

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Tables

Table 1: Descriptive statistics

This table presents descriptive statistics on comment characteristics (Panel A), follower characteristics (Panel B), performance characteristics (Panel C), portfolio characteristics (Panel D), and trader characteristics (Panel E). Appendix A provides detailed descriptions of all variables used throughout the study.

	Mean	Min	Median	Max	Std. dev.	N
Panel A: Comment characteristics						
Comment (d)	0.040	0.000	0.000	1.000	0.196	475,288
# comments	1.54	1.00	1.00	30.00	1.23	19,004
# words per comment	38.54	5.00	22.00	1,024.00	52.99	19,004
% positive words	4.90	0.00	4.17	42.86	4.93	19,004
% negative words	1.63	0.00	0.00	33.33	2.92	19,004
Panel B: Follower characteristics						
Trade size (EUR)	5,360	0	2,237	324,587	11,266	43,676
Net investments (EUR)	107	-1239722	0	1,402,852	6,744	475,288
Panel C: Performance characteristics						
Return (%)	-0.007	-99.940	-0.003	304.911	2.653	475,288
Alpha (%)	-0.024	-100.730	-0.008	342.086	2.215	412,819
Panel D: Portfolio characteristics						
# followers	8	0	0	1,438	57	475,288
Funds of followers (EUR)	33,536	0	0	8,299,194	268,262	475,288
Age (days)	263	1	221	886	198	475,288
Real money account (d)	0.134	0.000	0.000	1.000	0.340	475,288
# securities	11.76	0.00	8.00	71.00	12.61	475,288
% stocks	56.97	0.00	67.21	134.60	38.04	418,328
% funds	18.87	0.00	0.00	199.72	31.26	418,328
% derivatives	0.90	0.00	0.00	102.25	6.89	418,328
% cash	20.75	-99.72	7.50	100.00	27.05	418,328
# trades	0.90	0.00	0.00	18.00	2.79	475,288
Turnover (%)	2.67	0.00	0.00	75.88	10.31	475,288
Panel E: Trader characteristics						
Professional (d)	0.012	0.000	0.000	1.000	0.108	475,288
Experienced (d)	0.945	0.000	1.000	1.000	0.228	475,288
Female (d)	0.027	0.000	0.000	1.000	0.162	475,288
# portfolios	2.49	1.00	2.00	11.00	1.80	475,288

Table 2: Determinants of comments

This table presents the results from a logit regression with day fixed effects (Column 1) and OLS regressions with day fixed effects (Columns 2 to 5). The dependent variable is either a dummy variable that equals one on days on which traders post at least one comment, and zero otherwise (Column 1), the logarithm of the number of posted comments (Column 2), the logarithm of the number of words per comment (Column 3), the fraction of positive words per comment (Column 4), or the fraction of negative words per comment (Column 5). In Column 1, we report marginal effects. In Columns 2 to 5, we restrict the sample to days with at least one posted comment. Appendix A provides detailed descriptions of all variables used throughout the study. Standard errors are clustered at the portfolio level. t-statistics are provided in parentheses. ***, **, * denote statistical significance at the 1%, 5%, 10% level.

	Comment (d)	Log(# comments)	Log(# words per comment)	% positive words	% negative words
	(1)	(2)	(3)	(4)	(5)
Return (%)$_{t-1}$	0.002***	0.008***	-0.013**	0.147***	-0.018
	(7.59)	(4.13)	(-2.16)	(4.81)	(-1.08)
Log(net investments)$_{t-1}$	0.001***	0.003***	0.004	0.004	0.003
	(3.17)	(3.30)	(0.97)	(0.28)	(0.36)
Log(funds of followers)$_{t-1}$	0.003***	0.000	0.031***	-0.033*	0.013
	(9.37)	(0.14)	(4.72)	(-1.92)	(1.27)
Log(age)	-0.011***	-0.018***	-0.019	-0.031	-0.028
	(-18.17)	(-4.73)	(-1.10)	(-0.61)	(-0.95)
Real money account$_{t-1}$ (d)	0.015**	-0.014	0.026	-0.050	-0.323**
	(2.22)	(-0.75)	(0.25)	(-0.14)	(-2.05)
# securities$_{t-1}$	0.000***	0.001**	-0.004	0.012	0.003
	(3.26)	(2.18)	(-1.45)	(1.43)	(0.45)
Turnover (%)$_{t-1}$	0.000***	0.002***	0.001	-0.002	0.004**
	(5.15)	(4.70)	(0.60)	(-0.64)	(2.06)
Professional (d)	0.013	-0.077***	-0.183	0.459*	0.640***
	(0.94)	(-3.34)	(-1.06)	(1.72)	(4.00)
Experienced (d)	0.007	0.010	0.078	0.147	-0.030
	(0.90)	(0.29)	(0.83)	(0.42)	(-0.15)
Female (d)	0.014	-0.065***	0.782***	-0.285	-0.280***
	(1.36)	(-3.30)	(4.15)	(-1.41)	(-2.62)
# portfolios$_{t-1}$	-0.000	-0.001	-0.019	-0.128***	-0.035
	(-0.04)	(-0.14)	(-1.19)	(-3.10)	(-1.36)
Constant		1.003***	3.112***	8.863***	0.976**
		(8.59)	(12.99)	(3.90)	(2.45)
Day fixed effects	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.063				
Adj. R^2		0.023	0.102	0.015	0.008
N	475,288	19,004	19,004	19,004	19,004

Table 3: Comments and transactions of followers

This table presents the results from panel regressions with portfolio and day fixed effects. The dependent variable is the inverse hyperbolic sine of daily net investments of followers. In Column 2, the variables *Return (%)$_{t-1}$*, *Return (%)$_{t-2}$*, *Return (%)$_{t-3}$*, *Return (%)$_{t-4}$*, *Return (%)$_{t-5}$*, *Past 1-month return (%)$_{t-1}$*, *Past 3-month return (%)$_{t-1}$*, *Past 6-month return (%)$_{t-1}$*, *Past 1-year return (%)$_{t-1}$*, *Return since inception (%)$_{t-1}$*, *Log(net investments)$_{t-1}$*, *Log(net investments)$_{t-2}$*, *Log(net investments)$_{t-3}$*, *Log(net investments)$_{t-4}$*, *Log(net investments)$_{t-5}$*, *Log(funds of followers)$_{t-1}$*, *Log(age)*, *Real money account (d)$_{t-1}$*, *# securities$_{t-1}$*, *Turnover (%)$_{t-1}$*, *Professional (d)*, *Experienced (d)*, *Female (d)*, and *# portfolios$_{t-1}$* are included as controls but not reported. In Column 3, we include the same set of controls expect for the variables *Professional (d)*, *Experienced (d)*, *Female (d)* that are captured by the portfolio fixed effects. Appendix A provides detailed descriptions of all variables used throughout the study. Standard errors are clustered at the portfolio level. t-statistics are provided in parentheses. ***, **, * denote statistical significance at the 1%, 5%, 10% level.

	Log(net investments)		
	(1)	(2)	(3)
Comment (d)$_{t-1}$	0.309***	0.081***	0.067**
	(6.00)	(3.27)	(2.20)
Constant	0.057***	0.158***	0.938***
	(8.90)	(7.73)	(3.78)
Controls	No	Yes	Yes
Portfolio fixed effects	No	No	Yes
Day fixed effects	No	No	Yes
Adj. R^2	0.001	0.124	0.130
N	475,288	475,288	475,288

Table 4: Comments, investments, and withdrawals

This table presents the results from panel regressions with portfolio and day fixed effects. The dependent variable is either the inverse hyperbolic sine of daily investments (Column 1) or the inverse hyperbolic sine of daily withdrawals of followers (Column 2). The variables *Return (%)*$_{t-1}$, *Return (%)*$_{t-2}$, *Return (%)*$_{t-3}$, *Return (%)*$_{t-4}$, *Return (%)*$_{t-5}$, *Past 1-month return (%)*$_{t-1}$, *Past 3-month return (%)*$_{t-1}$, *Past 6-month return (%)*$_{t-1}$, *Past 1-year return (%)*$_{t-1}$, *Return since inception (%)*$_{t-1}$, *Log(net investments)*$_{t-1}$, *Log(net investments)*$_{t-2}$, *Log(net investments)*$_{t-3}$, *Log(net investments)*$_{t-4}$, *Log(net investments)*$_{t-5}$, *Log(funds of followers)*$_{t-1}$, *Log(age)*, *Real money account (d)*$_{t-1}$, *# securities*$_{t-1}$, *Turnover (%)*$_{t-1}$, and *# portfolios*$_{t-1}$ are included as controls in every regression but not reported. Appendix A provides detailed descriptions of all variables used throughout the study. Standard errors are clustered at the portfolio level. t-statistics are provided in parentheses. ***, **, * denote statistical significance at the 1%, 5%, 10% level.

	Log(investments)	Log(withdrawals)
	(1)	(2)
Comment (d)$_{t-1}$	0.124***	0.041**
	(5.19)	(2.38)
Constant	0.980***	0.231
	(4.92)	(1.25)
Controls	Yes	Yes
Portfolio fixed effects	Yes	Yes
Day fixed effects	Yes	Yes
Adj. R^2	0.388	0.318
N	475,288	475,288

Table 5: Comments and transactions of followers in the longer run

This table presents the results from panel regressions with portfolio and day fixed effects. The dependent variable is the inverse hyperbolic sine of average daily net investments of followers. We compute average daily net investments for each week after the posting of a comment. The variables *Return (%)*$_{t\text{-}1}$, *Return (%)*$_{t\text{-}2}$, *Return (%)*$_{t\text{-}3}$, *Return (%)*$_{t\text{-}4}$, *Return (%)*$_{t\text{-}5}$, *Past 1-month return (%)*$_{t\text{-}1}$, *Past 3-month return (%)*$_{t\text{-}1}$, *Past 6-month return (%)*$_{t\text{-}1}$, *Past 1-year return (%)*$_{t\text{-}1}$, *Return since inception (%)*$_{t\text{-}1}$, *Log(net investments)*$_{t\text{-}1}$, *Log(net investments)*$_{t\text{-}2}$, *Log(net investments)*$_{t\text{-}3}$, *Log(net investments)*$_{t\text{-}4}$, *Log(net investments)*$_{t\text{-}5}$, *Log(funds of followers)*$_{t\text{-}1}$, *Log(age)*, *Real money account (d)*$_{t\text{-}1}$, *# securities*$_{t\text{-}1}$, *Turnover (%)*$_{t\text{-}1}$, and *# portfolios*$_{t\text{-}1}$ are included as controls in every regression but not reported. Appendix A provides detailed descriptions of all variables used throughout the study. Standard errors are clustered at the portfolio level. t-statistics are provided in parentheses. ***, **, * denote statistical significance at the 1%, 5%, 10% level.

	Log(net investments)							
	t,t+4 (week 1)	t+5,t+9 (week 2)	t+10,t+14 (week 3)	t+15,t+19 (week 4)	t+20,t+24 (week 5)	t+25,t+29 (week 6)	t+30,t+34 (week 7)	t+35,t+39 (week 8)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Comment (d)$_{t\text{-}1}$	0.168***	0.089**	0.096**	0.065	0.035	0.030	-0.037	-0.016
	(4.33)	(2.03)	(1.99)	(1.24)	(0.72)	(0.62)	(-0.73)	(-0.38)
Constant	1.314***	1.503***	1.034***	0.952***	0.772**	0.932***	0.727***	0.483
	(4.42)	(4.86)	(3.19)	(3.09)	(2.46)	(3.18)	(2.71)	(1.52)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Portfolio fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.173	0.129	0.105	0.089	0.082	0.077	0.074	0.072
N	466,652	456,136	445,893	435,659	425,586	415,857	406,156	396,478

Table 6: Number of comments, length of comments, comment tone, and transactions of followers

This table presents the results from panel regressions with portfolio and day fixed effects. The dependent variable is the inverse hyperbolic sine of daily net investments of followers. We restrict the sample to days with at least one comment posted on the preceding day. The variables *Return (%)*$_{t-1}$, *Return (%)*$_{t-2}$, *Return (%)*$_{t-3}$, *Return (%)*$_{t-4}$, *Return (%)*$_{t-5}$, *Past 1-month return (%)*$_{t-1}$, *Past 3-month return (%)*$_{t-1}$, *Past 6-month return (%)*$_{t-1}$, *Past 1-year return (%)*$_{t-1}$, *Return since inception (%)*$_{t-1}$, *Log(net investments)*$_{t-1}$, *Log(net investments)*$_{t-2}$, *Log(net investments)*$_{t-3}$, *Log(net investments)*$_{t-4}$, *Log(net investments)*$_{t-5}$, *Log(funds of followers)*$_{t-1}$, *Log(age)*, *Real money account (d)*$_{t-1}$, *# securities*$_{t-1}$, *Turnover (%)*$_{t-1}$, and *# portfolios*$_{t-1}$ are included as controls in every regression but not reported. Appendix A provides detailed descriptions of all variables used throughout the study. Standard errors are clustered at the portfolio level. t-statistics are provided in parentheses. ***, **, * denote statistical significance at the 1%, 5%, 10% level.

	Log(net investments)				
	(1)	(2)	(3)	(4)	(5)
Log(# comments)$_{t-1}$	0.092				0.094
	(1.12)				(1.14)
Log(# words per comment)$_{t-1}$		0.020			0.021
		(0.51)			(0.55)
% positive words$_{t-1}$			0.008*		0.008*
			(1.91)		(1.84)
% negative words$_{t-1}$				-0.007	-0.006
				(-0.89)	(-0.75)
Constant	4.224***	4.233***	4.269***	4.313***	3.944**
	(2.75)	(2.71)	(2.75)	(2.78)	(2.48)
Controls	Yes	Yes	Yes	Yes	Yes
Portfolio fixed effects	Yes	Yes	Yes	Yes	Yes
Day fixed effects	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.169	0.169	0.170	0.169	0.169
N	19,190	19,190	19,190	19,190	19,190

Table 7: The predictive power of comments for future performance

This table presents the results from panel regressions with portfolio and day fixed effects. The dependent variable is either the daily raw return (Columns 1, 3, 5, 7, 9, and 11) or the daily alpha of portfolios (Columns 2, 4, 6, 8, 10, and 12). In Columns 3 to 12, we restrict the sample to days with at least one comment posted on the preceding day. Daily alphas are calculated as the difference between daily raw returns and predicted returns using a four-factor model. The factor exposures used to predict returns are estimated over 6-month rolling windows from t-126 to t-1. The four-factor model includes the MSCI Europe Index as proxy for the market, a SMB factor (return difference between the MSCI Europe Small Cap Index and the MSCI Europe Index), a HML factor (return difference between the MSCI Europe Value Index and the MSCI Europe Growth Index), and a momentum factor (MSCI Europe Momentum Index). The variables *Return (%)$_{t-1}$*, *Return (%)$_{t-2}$*, *Return (%)$_{t-3}$*, *Return (%)$_{t-4}$*, *Return (%)$_{t-5}$*, *Past 1-month return (%)$_{t-1}$*, *Past 3-month return (%)$_{t-1}$*, *Past 6-month return (%)$_{t-1}$*, *Past 1-year return (%)$_{t-1}$*, *Return since inception (%)$_{t-1}$*, *Log(net investments)$_{t-1}$*, *Log(net investments)$_{t-2}$*, *Log(net investments)$_{t-3}$*, *Log(net investments)$_{t-4}$*, *Log(net investments)$_{t-5}$*, *Log(funds of followers)$_{t-1}$*, *Log(age)*, *Real money account (d)$_{t-1}$*, *# securities$_{t-1}$*, *Turnover (%)$_{t-1}$*, and *# portfolios$_{t-1}$* are included as controls in every regression but not reported. Appendix A provides detailed descriptions of all variables used throughout the study. Standard errors are clustered at the portfolio level. t-statistics are provided in parentheses. ***, **, * denote statistical significance at the 1%, 5%, 10% level.

	Return (%)	Alpha (%)	Return (%)	Alpha (%)	Return (%)	Alpha (%)	Return (%)	Alpha (%)	Return (%)	Alpha (%)	Return (%)	Alpha (%
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Comment (d)$_{t-1}$	0.010	-0.013										
	(0.54)	(-0.86)										
Log(# comments)$_{t-1}$			-0.080	-0.060							-0.080	-0.059
			(-1.42)	(-1.29)							(-1.42)	(-1.29)
Log(# words per comment)$_{t-1}$					0.012	0.012					0.013	0.013
					(0.54)	(0.54)					(0.57)	(0.55)
% positive words							0.005**	0.003			0.005**	0.003
							(2.14)	(1.00)			(2.17)	(1.03)
% negative words									-0.002	0.001	-0.001	0.001
									(-0.43)	(0.16)	(-0.26)	(0.27)
Constant	1.715***	0.756***	1.791*	0.449	1.678	0.342	1.698	0.365	1.725	0.381	1.723*	0.389
	(11.04)	(2.87)	(1.71)	(1.25)	(1.59)	(0.95)	(1.59)	(0.98)	(1.62)	(1.04)	(1.65)	(1.09)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Portfolio fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.066	0.046	0.112	0.111	0.112	0.111	0.112	0.111	0.112	0.111	0.112	0.111
N	475,288	412,819	19,190	15,364	19,190	15,364	19,190	15,364	19,190	15,364	19,190	15,364

Table 8: Performance of transactions of followers

This table presents the results from OLS regressions. The dependent variable is either the excess return of a follower-weighted calendar-time portfolio formed on portfolios of traders (Column 1), the excess return of an equal-weighted calendar-time portfolio formed on portfolios of traders (Column 2), or the return difference between the two portfolios (Column 3). The four-factor model includes the MSCI Europe Index as proxy for the market, a SMB factor (return difference between the MSCI Europe Small Cap Index and the MSCI Europe Index), a HML factor (return difference between the MSCI Europe Value Index and the MSCI Europe Growth Index), and a momentum factor (MSCI Europe Momentum Index). Standard errors are adjusted for heteroskedasticity. t-statistics are provided in parentheses. ***, **, * denote statistical significance at the 1%, 5%, 10% level.

	Excess return (%)		
	Follower-weighted portfolio	Equal-weighted portfolio	Difference portfolio
	(1)	(2)	(3)
Alpha (%)	-0.027	-0.031**	0.004
	(-1.34)	(-2.19)	(0.25)
Market excess return	0.464***	0.424***	0.040
	(7.21)	(8.36)	(0.90)
SMB	0.352***	0.239***	0.113***
	(6.32)	(5.47)	(3.05)
HML	0.211***	0.172***	0.040
	(2.87)	(3.06)	(0.82)
Momentum	0.135***	0.095**	0.040
	(2.94)	(2.43)	(1.34)
Adj. R^2	0.533	0.645	0.041
N	506	506	506

Table 9: Which traders drive results?

This table presents the results from panel regressions with portfolio and day fixed effects. The dependent variable is either the inverse hyperbolic sine of daily net investments of followers (Column 1), the daily raw return (Column 2), or the daily alpha of portfolios (Column 3). Daily alphas are calculated as the difference between daily raw returns and predicted returns using a four-factor model. The factor exposures used to predict returns are estimated over 6-month rolling windows from t-126 to t-1. The four-factor model includes the MSCI Europe Index as proxy for the market, a SMB factor (return difference between the MSCI Europe Small Cap Index and the MSCI Europe Index), a HML factor (return difference between the MSCI Europe Value Index and the MSCI Europe Growth Index), and a momentum factor (MSCI Europe Momentum Index). The variables *Return (%)*$_{t-1}$, *Return (%)*$_{t-2}$, *Return (%)*$_{t-3}$, *Return (%)*$_{t-4}$, *Return (%)*$_{t-5}$, *Past 1-month return (%)*$_{t-1}$, *Past 3-month return (%)*$_{t-1}$, *Past 6-month return (%)*$_{t-1}$, *Past 1-year return (%)*$_{t-1}$, *Return since inception (%)*$_{t-1}$, *Log(net investments)*$_{t-1}$, *Log(net investments)*$_{t-2}$, *Log(net investments)*$_{t-3}$, *Log(net investments)*$_{t-4}$, *Log(net investments)*$_{t-5}$, *Log(funds of followers)*$_{t-1}$, *Log(age)*, *Real money account (d)*$_{t-1}$, *# securities*$_{t-1}$, *Turnover (%)*$_{t-1}$, and *# portfolios*$_{t-1}$ are included as controls in every regression but not reported. Appendix A provides detailed descriptions of all variables used throughout the study. Standard errors are clustered at the portfolio level. t-statistics are provided in parentheses. ***, **, * denote statistical significance at the 1%, 5%, 10% level.

	Log(net investments)	Return (%)	Alpha (%)
	(1)	(2)	(3)
Comment (d)$_{t-1}$	0.110	0.106	0.055
	(0.66)	(1.30)	(0.62)
Comment (d)$_{t-1}$ × Return (%)$_{t-1}$	0.034***	0.019	-0.078
	(3.04)	(0.49)	(-1.22)
Comment (d)$_{t-1}$ × Log(net investments)$_{t-1}$	0.043**	-0.000	0.007
	(2.06)	(-0.02)	(1.36)
Comment (d)$_{t-1}$ × Log(funds of followers)$_{t-1}$	0.005	0.005	0.000
	(0.88)	(1.24)	(0.04)
Comment (d)$_{t-1}$ × Log(age)	-0.059***	-0.003	0.012
	(-2.67)	(-0.17)	(0.77)
Comment (d)$_{t-1}$ × Real money account (d)$_{t-1}$	0.107	-0.027	0.000
	(0.84)	(-0.69)	(0.01)
Comment (d)$_{t-1}$ × # securities$_{t-1}$	-0.002	-0.001	0.000
	(-1.48)	(-0.90)	(0.28)
Comment (d)$_{t-1}$ × Turnover (%)$_{t-1}$	0.004**	0.002	0.002
	(2.28)	(0.98)	(0.63)
Comment (d)$_{t-1}$ × Professional (d)$_{t-1}$	0.108	0.013	0.006
	(0.80)	(0.44)	(0.16)
Comment (d)$_{t-1}$ × Experienced (d)	0.205*	-0.107**	-0.120**
	(1.70)	(-2.43)	(-2.46)
Comment (d)$_{t-1}$ × Female (d)$_{t-1}$	-0.026	0.008	0.026
	(-0.19)	(0.25)	(0.84)
Comment (d)$_{t-1}$ × # portfolios$_{t-1}$	-0.013	-0.005	-0.011
	(-0.64)	(-0.48)	(-1.05)
Constant	0.917***	1.713***	0.761***
	(3.70)	(10.98)	(2.88)
Controls	Yes	Yes	Yes
Portfolio fixed effects	Yes	Yes	Yes
Day fixed effects	Yes	Yes	Yes
Adj. R^2	0.130	0.066	0.046
N	475,288	475,288	412,819

Table 10: Which followers drive results?

This table presents the results from panel regressions with portfolio and day fixed effects. The dependent variable is the inverse hyperbolic sine of daily net investments of followers. In Columns 1 and 3, we restrict the sample to small trades and in Columns 2 and 4 to large trades. We classify trades as small trades if they are smaller than or equal to EUR 5,000 (EUR 2,500) and as large trades if they are larger than EUR 5,000 (EUR 2,500). The variables *Return (%)$_{t-1}$*, *Return (%)$_{t-2}$*, *Return (%)$_{t-3}$*, *Return (%)$_{t-4}$*, *Return (%)$_{t-5}$*, *Past 1-month return (%)$_{t-1}$*, *Past 3-month return (%)$_{t-1}$*, *Past 6-month return (%)$_{t-1}$*, *Past 1-year return (%)$_{t-1}$*, *Return since inception (%)$_{t-1}$*, *Log(net investments)$_{t-1}$*, *Log(net investments)$_{t-2}$*, *Log(net investments)$_{t-3}$*, *Log(net investments)$_{t-4}$*, *Log(net investments)$_{t-5}$*, *Log(funds of followers)$_{t-1}$*, *Log(age)*, *Real money account (d)$_{t-1}$*, *# securities$_{t-1}$*, *Turnover (%)$_{t-1}$*, and *# portfolios$_{t-1}$* are included as controls in every regression but not reported. Appendix A provides detailed descriptions of all variables used throughout the study. Standard errors are clustered at the portfolio level. t-statistics are provided in parentheses. ***, **, * denote statistical significance at the 1%, 5%, 10% level.

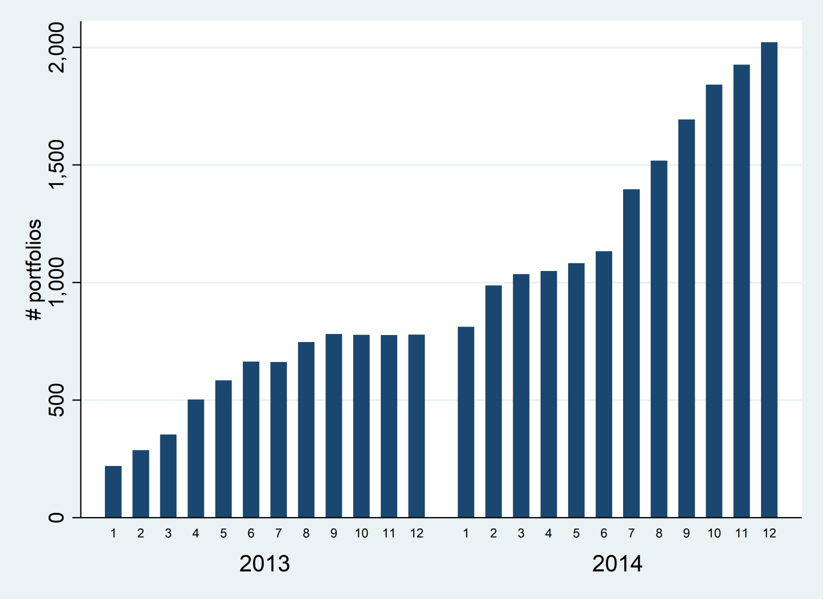
	Log(net investments)			
	EUR 5,000 as cutoff		EUR 2,500 as cutoff	
	Small trades	Large trades	Small trades	Large trades
	(1)	(2)	(3)	(4)
Comment (d)$_{t-1}$	0.064***	0.001	0.057***	0.027
	(2.58)	(0.05)	(2.81)	(1.01)
Constant	0.962***	0.236	0.827***	0.459**
	(4.64)	(1.30)	(3.98)	(2.30)
Controls	Yes	Yes	Yes	Yes
Portfolio fixed effects	Yes	Yes	Yes	Yes
Day fixed effects	Yes	Yes	Yes	Yes
Adj. R^2	0.137	0.082	0.123	0.109
N	475,288	475,288	475,288	475,288

Figures

Figure 1: Number of portfolios and follower funds

This figure shows the number of portfolios (Panel A) as well as the amount of follower money that replicates investment decisions of traders (Panel B) in our sample in the time period from January 2013 to December 2014.

Panel A: Number of portfolios



Panel B: Follower funds

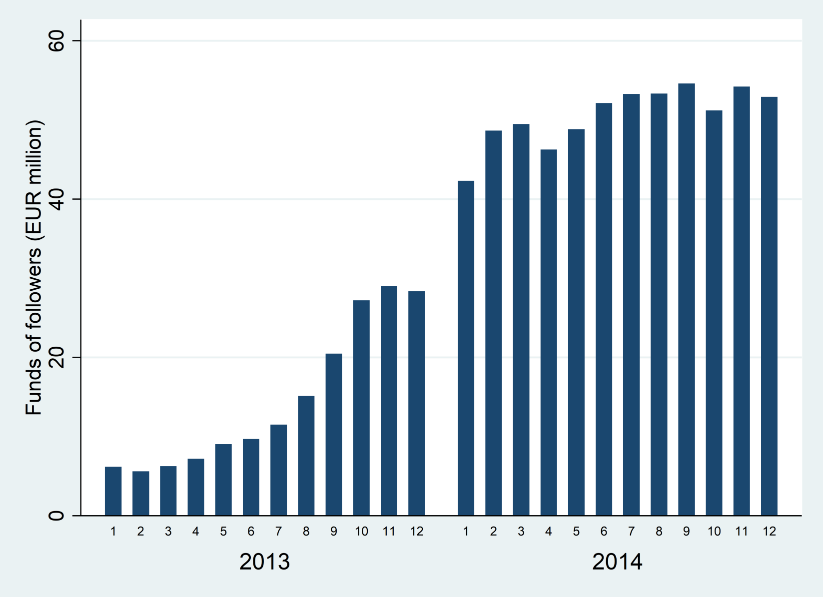


Figure 2: Sample comments

This figure shows six sample comments published on our social trading platform, of which three are firm-specific comments (Panel A) and the other three are general comments (Panel B). To identify positive and negative words in comments, we use word lists that are based on the Harvard IV-4 dictionary (Remus et al., 2010). Positive and negative words that are included in our dictionary are underlined. We provide one possible translation of comments.

Panel A: Firm-specific comments

April 24, 2014, regarding GlaxoSmithKline (GB0009252882):
I'm selling GlaxoSmithKline with a gain of 2%. Over the last couple of days, prices of major pharma stocks have increased substantially in the course of merger fantasies. I'm using this opportunity to exit.

March 19, 2013, regarding Apple (US0378331005):
Apple is expected to release good quarterly results.

October 29, 2014, regarding Cancom (DE0005419105):
Last night, Cancom reported extremely strong results: Revenues climbed by 46.5% to EUR 208.4 million in the third quarter and the earnings before interest, taxes, depreciation and amortization (EBITDA) rose by 93.8% to EUR 15.5 million, boosting the EBITDA margin to 7.4% from 5.6%. In the first nine months of the year, Cancom reported a revenue increase of 39.7% to EUR 583.1 million and the EBITDA rose by almost 65% to EUR 37.6 million. Given these great preliminary figures, I am looking forward to the full report, which is going to be released on November 11. In the past, I pointed out several times that this an excellent investment opportunity. I expect the stock to remain on a tear.

Panel B: General comments

June 7, 2013:
Due to the protests in Turkey the performance of the Lyxor ETF Turkey deteriorated. However, as the overall economic environment has not changed, I'm keeping it as 5% of my portfolio.

June 5, 2014:
An exciting day lies ahead of us: This afternoon, the ECB will announce additional monetary policy measures. They may push the DAX above 10,000 points if the measures go beyond market expectations.

August 22, 2014:
Investing in the stock market is currently a tough business. However, the portfolio is still on track to generate a target return of 26% p.a. To date, the annualized return is about 25.7%. Just to remind you, an annual return of about 26% implies that the value of the portfolio doubles every three years. Still, the performance of the portfolio heavily depends on only a few stocks. Recently, Norma and SHW have performed rather poorly. However, as I cannot identify anything negative in their fundamentals I am leaving my portfolio as it is.

Appendix

Appendix A: Variable descriptions

This table defines the variables used throughout the study.

Variable	Description
Comment characteristics	
Comment (d)	Dummy variable that equals one on days on which traders post at least one comment, and zero otherwise
# comments	Number of comments posted by a trader on a certain day
Log(# comments)	$Ln(\#\ comments)$
# words per comment	Number of words per comment; if there are multiple comments per day, we take the average across all comments
Log(# words per comment)	$Ln(\#\ words\ per\ comment)$
% positive words	Number of positive words per comment / Number of words per comment; if there are multiple comments per day, we take the average across all comments
% negative words	Number of negative words per comment / Number of words per comment; if there are multiple comments per day, we take the average across all comments
Follower characteristics	
Trade size (EUR)	Trade size (in EUR)
Net investments (EUR)	Daily net investments of followers into a trading strategy (in EUR)
Log(net investments)	$Ln(Net\ investments + \sqrt{Net\ investments^2 + 1})$ (inverse hyperbolic sine of net investments)
Performance characteristics	
Return (%)	Daily raw returns of a portfolio net of transaction costs and fees
Alpha (%)	Daily alphas are calculated as the difference between daily raw returns and returns predicted using a four-factor model. The factor exposures used to predict returns are estimated over 6-month rolling windows from t-126 to t-1. The four-factor model includes the MSCI Europe Index as proxy for the market, a SMB factor (return difference between the MSCI Europe Small Cap Index and the MSCI Europe Index), a HML factor (return difference between the MSCI Europe Value Index and the MSCI Europe Growth Index), and a momentum factor (MSCI Europe Momentum Index)
Past 1-month return (%)	Raw return of a portfolio net of transaction costs and fees over the past month
Past 3-month return (%)	Raw return of a portfolio net of transaction costs and fees over the past three months
Past 6-month return (%)	Raw return of a portfolio net of transaction costs and fees over the past six months
Past 1-year return (%)	Raw return of a portfolio net of transaction costs and fees over the past year
Return since inception (%)	Raw return of a portfolio net of transaction costs and fees since its creation
Portfolio characteristics	
# followers	Number of individuals who have allocated capital to a trading strategy
Funds of followers (EUR)	Amount of money that replicates a trading strategy (in EUR)

Log(funds of followers)	$Ln(funds\ of\ followers)$
Age (days)	Number of calendar days since the creation of a portfolio
Log(age)	$Ln(age)$
Real money account (d)	Dummy variable that equals one if the trader manages a real money portfolio, and zero otherwise
# securities	Number of securities in a trader's portfolio; winsorized at the 99% level
% stocks	Value of stocks in a trader's portfolio / Portfolio size
% funds	Value of mutual funds and exchange-traded funds in a trader's portfolio / Portfolio size
% derivatives	Value of derivative instruments in a trader's portfolio / Portfolio size
% cash	Cash position in a trader's portfolio / Portfolio size
# trades	Number of trades in a trader's portfolio on a given day; winsorized at the 99% level
Turnover (%)	$\frac{1}{2}$ (Value of all purchases executed in a trader's portfolio on a certain day + Value of all sales executed in a trader's portfolio on a certain day) / Portfolio size at the beginning of the day; winsorized at the 99% level
Trader characteristics	
Professional (d)	Dummy variable that equals one if the trader is a professional asset management firm as verified by the platform, and zero otherwise
Experienced (d)	Dummy variable that equals one for traders who claim to have more than three years of trading experience, and zero otherwise
Female (d)	Dummy variable that equals one for female traders, and zero otherwise
# portfolios	Number of portfolios managed by a trader

Appendix B: Results from robustness tests

Table A1: Most frequently used positive and negative words

This table shows the 25 most frequently mentioned positive and negative words in traders' comments. To identify positive and negative words in comments, we use word lists that are based on the Harvard IV-4 dictionary (Remus et al., 2010). We provide one possible translation of words.

Rank	Positive words	Negative words
1	gain	unfortunately
2	up-to-date	tight
3	good	end
4	new	loss
5	value	small
6	gains	despite
7	strong	risk
8	correction	down
9	purchase	brief
10	positive	breakout
11	easy	slow
12	up	weakness
13	accomplished	reduced
14	target	reduce
15	recovery	downtrend
16	increase	negative
17	great	smaller
18	fast	low
19	better	difficult
20	power	poor
21	right	trouble
22	invest	drop
23	uptrend	decrease
24	rise	poorer
25	share	barrier

Table A2: Comments and transactions of followers – firm-specific vs. general comments

This table presents the results from panel regressions with portfolio and day fixed effects. The dependent variable is the inverse hyperbolic sine of daily net investments of followers in trading strategies. In Columns 1 to 6, we restrict the sample to firm-specific comments and in Columns 7 to 12 to general comments. Moreover, in Columns 2 to 6 and Columns 8 to 12, we focus on days with at least one comment posted on the preceding day. The variables *Return (%)*$_{t-1}$, *Return (%)*$_{t-2}$, *Return (%)*$_{t-3}$, *Return (%)*$_{t-4}$, *Return (%)*$_{t-5}$, *Past 1-month return (%)*$_{t-1}$, *Past 3-month return (%)*$_{t-1}$, *Past 6-month return (%)*$_{t-1}$, *Past 1-year return (%)*$_{t-1}$, *Return since inception (%)*$_{t-1}$, *Log(net investments)*$_{t-1}$, *Log(net investments)*$_{t-2}$, *Log(net investments)*$_{t-3}$, *Log(net investments)*$_{t-4}$, *Log(net investments)*$_{t-5}$, *Log(funds of followers)*$_{t-1}$, *Log(age)*, *Real money account (d)*$_{t-1}$, *# securities*$_{t-1}$, *Turnover (%)*$_{t-1}$, and *# portfolios*$_{t-1}$ are included as controls in every regression but not reported. Appendix A provides detailed descriptions of all variables used throughout the study. Standard errors are clustered at the portfolio level. t-statistics are provided in parentheses. ***, **, * denote statistical significance at the 1%, 5%, 10% level.

	Log(net investments)											
	Firm-specific comments						General comments					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Comment (d)$_{t-1}$	0.018						0.078**					
	(0.40)						(2.33)					
Log(# comments)$_{t-1}$		-0.107				-0.101		-0.097				-0.099
		(-0.92)				(-0.88)		(-0.57)				(-0.57)
Log(# words per comment)$_{t-1}$			-0.072			-0.073			0.072			0.076
			(-0.88)			(-0.90)			(1.37)			(1.42)
% positive words$_{t-1}$				0.000		0.000				0.015**		0.014*
				(0.06)		(0.05)				(2.02)		(1.89)
% negative words$_{t-1}$					0.004	0.003					-0.020	-0.018
					(0.37)	(0.34)					(-1.30)	(-1.20)
Constant	0.923***	7.627***	7.783***	7.541***	7.535***	7.764***	0.838***	0.622	0.236	0.475	0.556	-0.190
	(3.67)	(3.38)	(3.51)	(3.37)	(3.37)	(3.81)	(3.44)	(0.61)	(0.23)	(0.48)	(0.55)	(-0.18)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Portfolio fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.125	0.183	0.183	0.183	0.183	0.182	0.125	0.145	0.145	0.145	0.145	0.146
N	464,244	8,146	8,146	8,146	8,146	8,146	465,675	9,577	9,577	9,577	9,577	9,577

Table A3: The predictive power of comments for future performance – 1-month performance

This table presents the results from panel regressions with portfolio and day fixed effects. The dependent variable is either the 1-month return (Columns 1, 3, 5, 7, 9, and 11) or the 1-month cumulative abnormal return (CAR) of trading strategies (Columns 2, 4, 6, 8, 10, and 12). In Columns 3 to 12, we restrict the sample to days with at least one comment posted on the preceding day. Daily abnormal returns are calculated as the difference between daily raw returns and predicted returns using a four-factor model. The factor exposures used to predict returns are estimated over 6-month rolling windows from t = -126 to t = -1. The four-factor model includes the MSCI Europe Index as proxy for the market, a SMB factor (return difference between the MSCI Europe Small Cap Index and the MSCI Europe Index), a HML factor (return difference between the MSCI Europe Value Index and the MSCI Europe Growth Index), and a momentum factor (MSCI Europe Momentum Index). The variables *Return (%)*$_{t-1}$, *Return (%)*$_{t-2}$, *Return (%)*$_{t-3}$, *Return (%)*$_{t-4}$, *Return (%)*$_{t-5}$, *Past 1-month return (%)*$_{t-1}$, *Past 3-month return (%)*$_{t-1}$, *Past 6-month return (%)*$_{t-1}$, *Past 1-year return (%)*$_{t-1}$, *Return since inception (%)*$_{t-1}$, *Log(net investments)*$_{t-1}$, *Log(net investments)*$_{t-2}$, *Log(net investments)*$_{t-3}$, *Log(net investments)*$_{t-4}$, *Log(net investments)*$_{t-5}$, *Log(funds of followers)*$_{t-1}$, *Log(age)*, *Real money account (d)*$_{t-1}$, *# securities*$_{t-1}$, *Turnover (%)*$_{t-1}$, and *# portfolios*$_{t-1}$ are included as controls in every regression but not reported. Appendix A provides detailed descriptions of all variables used throughout the study. Standard errors are clustered at the portfolio level. t-statistics are provided in parentheses. ***, **, * denote statistical significance at the 1%, 5%, 10% level.

	1-month return (%)	1-month CAR (%)	1-month return (%)	1-month CAR (%)	1-month return (%)	1-month CAR (%)	1-month return (%)	1-month CAR (%)	1-month return (%)	1-month CAR (%)	1-month return (%)	1-month CAR (%)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Comment (d)$_{t-1}$	-0.027	0.218										
	(-0.20)	(0.65)										
Log(# comments)$_{t-1}$			0.133	0.125							0.124	0.120
			(0.58)	(0.89)							(0.54)	(0.85)
Log(# words per comment)$_{t-1}$					-0.117	-0.116					-0.111	-0.113
					(-1.38)	(-1.57)					(-1.31)	(-1.53)
% positive words							0.020**	0.007			0.020**	0.007
							(2.15)	(1.01)			(2.19)	(0.93)
% negative words									0.017	-0.000	0.020	0.001
									(1.32)	(-0.01)	(1.50)	(0.05)
Constant	1.271**	0.355	2.572	2.519	3.110*	3.047	2.599*	2.596	2.665*	2.628	2.863*	2.902
	(2.00)	(0.74)	(1.63)	(1.08)	(1.90)	(1.32)	(1.65)	(1.11)	(1.68)	(1.13)	(1.77)	(1.26)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Portfolio fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.272	0.190	0.548	0.387	0.548	0.387	0.548	0.387	0.548	0.387	0.548	0.387
N	433,615	433,615	17,488	17,488	17,488	17,488	17,488	17,488	17,488	17,488	17,488	17,488