# Too good to be true? – The influence of manager self-descriptions on investor behavior

Theresa Spickers, Gesa-Kristina Petersen

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#### Abstract

We show that investors base their decisions on perceptions of the responsible investment manager shaped by manager-written texts. Relying on a novel dataset of a European social trading platform including self-descriptions from portfolio managers, we show that a positive emotional tone of these descriptions lowers portfolio inflows. We find no significant differences in performance and risk taking of managers. By testing the underlying mechanism in an experiment, our results reveal that the use of positive tone leads to lower portfolio inflows because managers are perceived as less competent. Our results thus provide evidence of taste-based discrimination with investors misattributing less competence to managers.

JEL-Classification Codes: G02, G11

Keywords: Social Trading, Fund flows, Textual analysis, Stereotypes, Fund performance

Gesa-K. Petersen & Theresa Spickers, Munich School of Management, Ludwig-Maximilians-University Munich, Schackstraße 4, 80539 Munich. Gesa-K. Petersen and Theresa Spickers contributed equally to this article.

## Introduction

At the heart of philosophy and psychology lies the idea that the words a person uses reflects how that person thinks and feels. That is, not only what we say but also how we say it, gives insights on ourselves (Fast & Funder, 2008; Pennebaker, Mehl, & Niederhoffer, 2003; Schwartz et al., 2013; Park et al., 2015). In this paper we claim that written texts by managers (e.g. mutual fund managers, start-up teams, etc.) are used as a source of information about manager characteristics by investors. More specifically, we focus on the impression of the person that is shaped by the tone and writing style of the text. In line with recent literature in finance on textual tone analysis (for a review see Loughran & McDonald, 2016), we analyze positive and negative tone expressed by positive and negative emotional words.

Recent research shows that the majority of mutual fund investors believe it is important to know the identity of their fund managers (Kumar, Niessen-Ruenzi, & Spalt, 2015). In line with this, manager characteristics and resulting stereotypes influence mutual fund flows (Kumar et al., 2015; Niessen-Ruenzi & Ruenzi, 2015). Similarly, Bernstein, Korteweg, and Laws (2016) show that information on the professional background of start-up founders is crucial to facilitate interest of early-stage investors. This research shows that in different realms of finance, investors want to know specifically with whom they entrust their money to. They not only care about education and experience but also about the personal characteristics of managers. We aim to contribute to this by analyzing if the way managers describe themselves and their experience shapes investor impressions about their character, thus influencing investment behavior. To answer this question we use a novel dataset from a social trading platform. In addition, we test causal relationships and underlying mechanisms with the help of experimental data. The social trading platform follows the concept of mutual fund investing. Altogether, we have microdata on 4919 portfolios of 2749 distinct managers over a time period of 2012 - 2016, with 328 million € inflows in total. Portfolio managers can build a portfolio that is issued as a certificate, which investors can choose to invest in. The portfolio is only issued as a certificate if a certain number of investors state their willingness to invest in the portfolio. On the platform each portfolio manager gives a description of themselves, describing their investment experience, motives to manage a portfolio, and past investment performance. To assess the explicit information (i.e. years of experience, education, job, etc.), we manually code the information given in the texts. To further assess the implicit information each text contains, we run dictionary-based textual analyses on emotional tone. A unique characteristic of the texts in our dataset is that they are neither copyedited nor verified by the social trading platform and hence represent an unfiltered sample on managers' writing style (exemplary self-descriptions can be found in the appendix). In comparison, classic mutual fund filings are likely to be highly polished, might not be written by fund managers themselves, and have undergone screening by the legal department. We regress monthly portfolio (i.e. certificate) inflows on positive and negative emotional tone in self-descriptions, controlling for various portfolio, portfolio manager and basic linguistic characteristics. We find that a one percent increase in the share of expressed positive emotions decreases monthly portfolio inflows by about 5%, while we find no effect for negative expressed emotions. This shows that investors indeed use self-descriptions as a source of information for investments and that a more positive emotional tone lower investors' willingness to invest in the portfolio. We assume that investors form an impression about manager skill based on these texts, resulting in a more negative impression on managers' competence or intent (Fiske, Cuddy, Glick, & Xu, 2002) when a more positive emotional tone is used in self-descriptions.

To analyze whether the positive emotional tone relates to manager ability, we regress semiannual portfolio returns (gross returns as well as alphas and risk) on positive and negative emotional tone measures and control for portfolio characteristics. We find that none of the return or risk measures are significantly influenced by positive or negative emotional tone. These results imply that positive tone does not serve as a proxy for manager ability and investors hence irrationally invest in portfolios of those managers.

To be able to make causal inferences and learn about investors' impressions of managers based on emotional tone we conducted a 4x4 within-between-subjects experiment. Each participant was shown four different manager self-descriptions that were either positive, negative, or neutral (2x) in tone. Participants then decided whether they would be willing to invest in portfolios managed by the respective manager and were asked to divide 100% of their fictional amount to invest between all four managers. To measure participants' impression of managers, we asked participants to assess the perceived competence and intent, with competence and intent<sup>2</sup> being the two core dimensions of social cognition (Fiske, Cuddy, & Glick, 2007; Fiske et al., 2002.

In line with our previous results, our experimental results show that if the emotional tone of portfolio managers' self-descriptions is more positive, participants' willingness and the percentage share to invest into the manager's portfolio is significantly lowered. In addition, the results show that a more positive tone leads to significantly lower perceived manager competence. Remarkably, by calculating mediation analyses we even find that the lower perceived competence mediates (i.e. causes) the influence of positive tone on investment decisions.

 $<sup>^{2}</sup>$  The terms warmth and intent have been used interchangeably (cf. Fiske et al., 2002). We believe the term intent to be clearer and better understandable in the context of financial decision making, which is why we apply this term instead of the more prominent term warmth. ...

The results of both empirical and experimental datasets imply that investors indeed infer information about managers from textual characteristics of self-descriptions: an overly positive tone in such descriptions leads to lower perceived competence, resulting in lower fund inflows.

Our findings contribute to different research strands. First, the findings add to literature on mutual fund flows, where it was shown recently that ethnicity (Kumar et al., 2015) and gender (Niessen-Ruenzi & Ruenzi, 2015) influence mutual fund flows, most probably because they foster stereotypes regarding mutual fund managers. We add to this by showing that positive tone shapes investors' perception on managers' competence and hence influence influence influence. By this, we not only provide another important source on irrational influences making a fund more or less successful, but in addition, provide supportive evidence for the underlying mechanism.

Our paper further supports the literature reporting on the aim of investors to know their (fund) managers. Massa, Reuter, and Zitzewitz (2010) show that funds where the fund manager name is not displayed receive lower inflows. This result is in line with our finding that investors apply information on the fund manager, which also reflects a desire to know the manager. In addition, Bernstein et al. (2016) find that early-stage start-up investors are more likely to signal interest in the start-up if they receive information about the professional background of start-up founders.

Moreover, our paper adds to the growing literature on textual analysis in finance research. While most papers use tone analysis to uncover (investor) sentiment expressed by the author of the text (Tetlock, 2007; Das & Chen, 2007; Price, Doran, Peterson, & Bliss, 2012), we use it to proxy the perception of the author of the text.

In addition, our paper extends findings in the psychological literature on word use, perception and behavior. It has been primarily studied which emotional consequences, such as feelings of admiration, envy, pity or contempt, result from impressions on intent and competence (Cuddy, Fiske, & Glick, 2008; Fiske et al., 2007). Only very few studies investigate how the use of positive and negative emotional tone influence perception. Testing university students in a context-free setting ("tell us about yourself and what is going on in your life; just tell us about yourself, your classes, or your activities", Berry, Pennebaker, Mueller, & Hiller, 1997, p. 530), it was found that a negative emotional tone leads to a decrease of perceived intent and competence, while no effects were found for positive emotion words (Berry et al., 1997). However, in the context of investment decisions, and thus in a situation where rational and deliberate decisions are valued, we show that investors apparently regard a positive tone as incompetent, and hence avoid investing in such a manager. Moreover, it was found in the context of consumer decisions that perceived positive intent and competence of a brand positively influences consumers' willingness to purchase goods from that brand (Aaker, Garbinsky, & Vohs, 2012). Our results are in line with this research: We show in the context of financial decisions that intent and competence positively relate to purchase decisions.

Last, our paper is among the first papers (next to e.g. Heimer, 2016) to shed light on the behavior and dynamics of investors on social trading platforms as well as in fintechs in general.

#### **Evidence from social trading platform**

#### The social trading platform

Our study is based on data from a European social trading platform. Social trading generally follows the idea that investors can track or mirror investment decisions by other investors. Our platform is designed in a way that private or professional investors (we call them portfolio managers) can propose investment strategies and set up a portfolio accordingly which other

investors can choose to invest in. As soon as enough investors are willing to follow a manager's investment strategy, a certificate is being issued which exactly mirrors the value of the underlying portfolio. Investors can then invest in the certificate (i.e. the portfolio) through their online broker accounts.

In terms of transaction costs, portfolio managers earn a performance fee between 5-30 % fixed by the portfolio manager based on the high watermark principle. The performance fee is split between the social trading platform and the portfolio manager. In addition, investors pay a so called certificate fee of 0.95 % p.a. To further earn money portfolio managers can but are not obliged to invest money in their own portfolio.

The platform was established in 2012 and accumulated 382 million  $\in$  inflows as of June 2016. Our dataset includes all portfolios which were successfully issued as a certificate, leading to 4919 distinct portfolios covering a time period between 2012 to mid-2016. Panel A and B of Table 1 provide descriptive statistics about the portfolios and portfolio managers. It shows that the avgerage performance fee that is charged is 11.86% and the average age of a portfolio is 23.44 month. Interestingly, most portfolio managers manage more than one portfolio, with the average being 3.11. In addition, we manually coded the information in the manager self-descriptions to gain additional information on the managers (Panel B). It appears that for those managers who indicated information about their experience (n=1198) the average years of experience is 15.98 years. Further, the average manager age is 35 (n=111) and only 2% of managers are female. In addition, we find that 13% of managers have a job that is related to finance and investing (i.e. trader, financial advisor, investment banker) and about 10% of managers use a real that is not a fictional nickname.

# Data and descriptive statistics

In our analyses we focus on the influence of expressed positive and negative emotions (i.e. emotional positive and negative tone) on portfolio inflows. To determine the emotional tone we conduct a dictionary-based textual analysis that is implemented with the 2015 linguistic inquiry and word count software (LIWC) by Pennebaker, Boyd, Jordan, & Blackburn, 2015. The software tokenizes a text into its words and converts each word to its word stem (e.g. stocks  $\rightarrow$  stock; buying  $\rightarrow$  buy). Then the software compares each word with several predefined dictionaries on positive and negative emotions respectively. If a word matches one dictionary, the dictionary measure is incremented by one. For example, if the software encounters the word "good" it will increment the measure of the dictionary "positive emotions" by one. In the end, the dictionary with respect to the whole text. Since our entire manager self-descriptions are in German, we use German dictionaries for the LIWC software (Wolf et al., 2008). The dictionaries cover approx. 7,670 word stems.

We exclude all portfolios from the analysis where the number of words is smaller than 25, since a small number of words can strongly distort the share of positive or negative emotional words. This leads to an exclusion of 906 portfolios.

Panel C of Table 1 shows descriptive statistics of the textual analysis. It displays the basic linguistic dimensions related to text readability such as number of words, sentence length (measured as average number of words per sentence) and word complexity (measured as share of words with more than six letters) (Miller, 2010; Lawrence, 2013). We later control for these basic linguistic dimensions in our regression analyses. Manager self-descriptions on average consist of 112 words, with an average number of words per sentence of 15 words and a share of 34% of complex words (more than six letter words). With respect to the emotional tone, self-descriptions

are in general more positive than negative, with an average of 2.28% positive words compared to an average of 0.48% negative words. The appendix provides an overview of the most commonly used positive and negative emotional words.

[Insert table 1 here]

Looking at monthly inflows, our main dependent variable, the average monthly inflow is  $7,235.62 \in$  although many months and portfolios have no inflow.

#### **Regression results: Emotional tone and portfolio inflows**

To analyze how positive and negative tone of managers in their self-description influence portfolio inflows, we regress monthly portfolio inflows after emission of the certificate on emotional tone and various control variables since oftentimes there is no inflow in the portfolio, we conduct a logit analysis where the dependent variable is a dummy indicating whether or not there is any inflow in the portfolio. Further, we conduct an OLS regression with monthly inflows being the dependent variable. In both types of regressions, we control for text readability (i.e. word count, words per sentence, share of six-letter words), performance fee, portfolio age, number of managed portfolios by manager, pre-emission return and risk, one month lagged return and risk and one month lagged summed inflows minus summed outflows. Moreover, we include month and year fixed effects, style fixed effects (i.e. fundamental, technical or other analysis techniques) and available investments fixed effects (stocks, funds, certificates, ETFs, derivatives). In all regressions, we cluster standard errors at the portfolio level. Further, we include in a separate regression manager control variables such as years of manager experience, having a job in finance and revealing the own identity by using a real name. In addition, we included in this regression fixed effects for the portfolio being labeled as managed by a private investor, an asset manager, an exchange association, or a media institution.

Table 2 presents the results of the inflow regressions. We find a consistent and significant negative effect of positive emotional tone across all regression specifications. In the OLS regressions, all else equal inflows are between 4.5 to 5.5% smaller if the positive tone of the text increases by 1%. Notably, the coefficient for positive emotional tone increases if we additionally control for manager characteristics, which implies that it is unlikely that the effect is driven by manager characteristics. Based on the logistic regression figure 1 provides evidence that the probability that a portfolio receives any inflows constantly decreases with an increasing positive tone. Fixing all other variables at their means, the probability decreases from 24% to 11%. Overall, the results suggest that a more positive tone leads to smaller investments in the portfolio. This is likely due to a taste-based discrimination of investors, who feel that a highly positive manager is dubious and less trustworthy.

[Insert table 2 and figure 1 here]

# **Regression results: Emotional tone and portfolio performance**

To rule out the alternative explanation that a more positive tone of managers' self-descriptions reflects lower manager ability or personality traits, we analyze whether positive or negative tone of self-descriptions predict portfolio performance and riskiness. To do so we compute the semi-annual return and portfolio alphas (1-,3-,4- and 5-factor alpha) and standard deviation based on semi-annual daily returns. The 1-factor alpha is based on the capital asset pricing model (CAPM), the 3-factor alpha is based on the Fama and French three-factor model (Fama & French, 1993), the 4-factor alpha adds the momentum factor by Carhart (1997), and the 5-factor alpha is based

on the Fama and French five-factor model (Fama & French, 2016).<sup>3</sup> Alpha is estimated as the intercept of the following regression (only those factors that are named above apply to the respective alpha):

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_i (R_{M,t} - R_{f,t}) + s_i SMB_t + h_i HML_t + m_i MOM_t \quad (2)$$
$$+ r_i RMW_t + c_i CMA_t + \varepsilon_{i,t}$$

where  $R_{i,t}$  is the return on fund i for day t,  $R_{f,t}$  is the risk-free rate,  $R_{M,t}$  is the market return, SMB<sub>t</sub> and HML<sub>t</sub> are the size and value-growth returns of Fama and French (1993), MOM<sub>t</sub> is the momentum factory by Carhart (1997), RMW<sub>t</sub> and CMA<sub>t</sub> are the profitability and investment factors of Fama and French (2016). Daily alphas are semi-annualized.

Table 3 displays the results of the performance regression. It shows that neither positive nor negative tone predict any of the return measures or the risk measure. Hence, we can infer that the influence of positive tone on portfolio inflows is not driven by manager ability indicating that investors seem to incorrectly avoid investing in portfolios of those managers.

[Insert table 3 here]

#### **Experimental evidence**

To test our hypothesis that investors perceive managers differently if they describe themselves more positively, we conducted an online experiment that is described in the following section. Relying on the two global dimensions of social perception, intent and competence (Fiske et al., 2002; Fiske et al., 2007), we hypothesized that managers should be perceived less warm and competent if investors decide to allocate less money to their portfolios. We hence assumed that if

<sup>&</sup>lt;sup>3</sup> We obtain the market, size, book-to-market, momentum, profitability and liquidity factors from Kenneth French's online data library (http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data\_library.html).

managers apply a more positive tone in their self-descriptions, investors perceive them as less competent and/or perceive their intent less positive, which then causes lower inflows.

#### Participants and Design

196 participants (102 women,  $M_{age} = 25$  years,  $SD_{age} = 8$  years) took part in this online experiment with a 4 (self-description of portfolio manager) x 4 (word use: positive emotions, negative emotions, control 1, control 2) within-between-subjects design (figure 2). 172 participants were students with 36 being enrolled in a program of the economic sciences or business administration. No experimental manipulations were eliminated and no participants were excluded from the sample. Participants were recruited with the help of a mailing list from a large German university as well as with the help of social networks. The online experiment lasted for about 15 minutes and one participant had the chance of winning EUR 170 for participating. Applying a-priori power analysis, we aimed to collect 195 participants (f = 0.1, required power = .95,  $\alpha = 0.05$ , N = 195).

### [Insert figure 2 here]

Participants always received four self-descriptions from all four portfolio managers but were randomly assigned to receiving the self-descriptions written in different tones. The textual tone was either completely neutral (control 1), neutral applying causal connectors (control 2), using positive emotion words (positive emotions) or negative emotion words (negative emotions). Descriptions were adapted from original self-descriptions of the empirical dataset of the first study. The different tone was added with regards to the most commonly used positive and negative emotion words based on the analysis of the empirical dataset (the text can be found in the Appendix). As a further control we tested our experimental manipulation with the LIWC computer program (Pennebaker et al., 2015) and extracted the percentage shares of positive and negative emotion words applied for each of the experimental conditions (Table 4).

[Insert table 4 here]

#### Procedure

After reading a general introduction to the study and accepting a consent form, participants were introduced to the following scenario: "Imagine you want to invest some of your money into shares. You therefore try a new platform, on which you can see the trades of other investors. You can then decide to invest exactly like one of the other investors. To better make your decision, you explore the profiles of these investors. Amongst other information, the profiles always provide a self-description of each investor." Thereafter, participants got to read the four selfdescriptions. Reading each description, we asked participants according to a seven-point likert scale whether they would be willing to invest like this investor with answers ranging from "not at all" to "yes for sure". The term "investors" of this study corresponds to the term portfolio manager in the empirical dataset. To measure participants' impression of the portfolio managers' character we adapted a scale on social perception by Fiske et al. (2002) measuring the perception of portfolio managers' intent (sincere, trustworthy, warm) and competence (competent, skilled, confident) on a five-point likert scale ranging from "not at all" to "entirely". Having received self-descriptions of all four portfolio managers, participants were asked to split 100% of their fictional investment between the four portfolio managers.

Participants then indicated their self-assessed financial knowledge on a visual analogue scale ranging from 0 to 100 and answered five questions to assess their basic financial literacy (Van Rooij, Lusardi, & Alessie, 2011). We asked participants to indicate demographics on their age, gender and educational level, as well as profession and whether they had answered the online

questionnaire on their smartphone, tablet, or computer. At the very end participants were invited to provide comments about the study and then thanked for their participation. Clicking on a separate link they could enter their e-mail address. We randomly selected one winner to receive the EUR 170 and contacted this participant via e-mail.

## **Experimental results**

## Does word use cause differences in investments?

To support the results from the social trading platform we regress both participants' willingness to copy portfolio managers' investments and the percentage share of investments on the use of positive emotion words and negative emotions words, including self-description and participant fixed effects to control for content-wise differences of manager descriptions and individual differences in preferences (Table 5, columns 1 & 2). The experimental results provide supportive evidence that word use causes differences in fund inflows. In line with the empirical data set, experimental results stress the negative effect of positive emotion word use for both dependent variables.

[Insert table 5 here]

# Do investors infer portfolio manager characteristics based on their writing style?

**Confirmatory factor analysis.** To get a two-dimensional measure on participants' overall perception of portfolio managers' intent (items: sincere, trustworthy, warm) and competence (items: competent, skilled and confident) we conduct a confirmatory factor analysis. Including both factors into our model, we receive good model fit when predicting intent (sincere, warm) and competence (competent, skilled) as latent variables ( $\chi^2 = 1.54$ , p = .21; CFI =1.00, TLI = 1.00, RMSEA = .03 [90% CI = .00, .10]). The items "trustworthy" and "confident" do not

sufficiently measure the intended latent variables, which is why they are deleted from analyses to achieve convergence and good model fit.

**Perceived intent and competence.** To analyze whether positive emotions indeed drive investor perceptions we regress both perceived intent and competence on the use of positive emotion words and negative emotions words, including self-description and participant fixed effects to control for content-wise differences of self-descriptions and individual differences in preferences (Table 5, columns 3 & 4). The experimental results show that word use causes differences in perception. While the use of positive emotion words makes participants perceive the portfolio manager to be less competent, the use of negative emotion words increases the perception of a good intent.

## Does word use influence investments due to differences in perception?

To answer this question we again regress both, participants' willingness to copy portfolio managers' investments and the percentage share of investments on the use of positive emotion words and negative emotions words including self-description and participant fixed effects to control for content-wise differences of self-descriptions and individual differences in preferences. In addition, we include intent and competence as independent variables (Table 5, columns 5 & 6). The results show that the effect of positive emotion words on the willingness to invest is severely reduced and the effect of positive emotion words on the percentage share of investments does not remain significant, when the independent variables intent and competence are included. Hence, both results suggest mediation effects.

We therefore conducted indirect effect analyses with the help of multilevel structural equation models. Controlling for repeated measurement, we tested whether the effect of positive emotions on the willingness to invest and on the percentage share of investments is caused by lower perceived competence. In both cases indirect effects show significant results (positive emotions, competence and willingness to invest: z = -4.98, p < 0.01, [95% CI = -.08, -0.03]; positive emotions, competence and percentage share of investment: z = -4.56, p < 0.01, [95% CI = -0.58, -0.23]), supporting the assumption that differences in investments due to word use are mediated by perception.

On a more general note our results show that both variables of social perception, intent and competence, positively predict investments.

#### Summary and conclusion

In this paper, we study whether perceptions on competence and intent, induced by emotional tone, affect investment choices in delegated portfolios. More precisely, we provide novel evidence that investors perceive portfolio manager skills differently due to the emotional tone of portfolio managers' self-descriptions. Our key finding is that a one percent increase in the share of expressed positive emotions decreases monthly portfolio inflows by about 5% because managers are perceived as being less competent. At the same time, analyses on performance show that the share of expressed positive emotions does not predict portfolio performance.

In an experimental setting in which we control for all other possible influences, individuals again allocate less money when a more positive emotional tone is added to managers' self-descriptions, emphasizing the idea of a taste-based discrimination against managers using positive emotional language. The results not only suggest but show that stereotypes and discrimination affect portfolio investments of investors.

In future work it may be interesting to examine if similar effects can be found for other investment forms, such as venture capital, and if effects differ for professional and private investors. With regards to consumer psychology it may be additionally interesting to investigate the effects of brand perception on stock performance.

# Figures



Figure 1: This figure displays the development of predicted probabilities by levels of positive emotional tone based on a logistic regression with the dependent variable being whether a portfolio attracts any inflows or not (if inflows > 0 the dummy = 1). All other independent variables are kept at their mean. The regression controls for one month lagged return, standard deviation, assets under management and various portfolio characteristics. It includes year, month, available investment and style fixed effects. Standard errors are robust and clustered by portfolio.

# Between

Within	Positive emotion	Negative emotion	Control 1	Control 2
Description 1	Participant 1	Participant 4	Participant 3	Participant 2
Description 2	Participant 2	Participant 1	Participant 4	Participant 3
Description 3	Participant 3	Participant 2	Participant 1	Participant 4
Description 4	Participant 4	Participant 3	Participant 2	Participant 1

Figure 2: Study design: 4 (self-description of portfolio manager) x 4 (word usage: positive emotions, negative emotions, control 1, control 2) within-between-subjects design

# Tables

**Table 1:** The table provides descriptive statistics of the portfolios (Panel A) and portfolio managers (Panel B) as well as emotional tone and basic linguistic dimensions of manager self-descriptions (Panel C). In Panel B manager characteristics are reported if available. In Panel C: WC = Number of words, WPS = Avg. number of words per sentence, Sixltr = Share of words with more than six letters.

Panel A - Portfolio characteristics									
Standard									
Mean	Median	Deviation	Min	p25	p75	Max	Ν		
11.86	10	7.41	5	5	15	30	4013		
23.44	21	11.68	6	15	29	52	4013		
No. of portfolios per									
3.20	2	2.55	1	1	4	18	4013		
7,235.63	0.00	89,241.34	0.00	0.00	0.00	12,400,000	65975		
-0.01	0.00	0.09	-0.56	-0.03	0.03	0.21	65975		
0.01	0.01	0.02	0.00	0.01	0.01	0.14	65957		
46,795.53	964.58	343,661.40	-40,434.86	0.00	10,092.81	11,700,000	65975		
Panel B - Manager characteristics									
		Standard							
Mean	Median	Deviation	Min	p25	p75	Max	Ν		
15.98	15	7.99	0	10	20	50	1198		
35.20	35	10.99	5	27	41	57	111		
0.02	0	0.12	0	0	0	1	772		
0.14	0	0.35	0	0	0	1	2116		
0.11	0	0.32	0	0	0	1	2116		
		Panel C - T	Tone analysis						
		Standard							
Mean	Median	Deviation	Min	p25	p75	Max	N		
112.99	78	109.15	26	44	133	714	2116		
15.24	14.47	5.66	5.25	11.54	17.6	40	2116		
34.54	34.635	6.82	6.67	29.835	39.53	60	2116		
2.26	2.11	1.93	0	0.465	3.39	12.77	2116		
0.48	0	0.89	0	0	0.78	8.93	2116		
	Mean 11.86 23.44 3.20 7,235.63 -0.01 0.01 46,795.53 Mean 15.98 35.20 0.02 0.14 0.11 12.99 15.24 34.54 2.26 0.48	Mean         Median           11.86         10           23.44         21           3.20         2           7,235.63         0.00           -0.01         0.00           0.01         0.01           46,795.53         964.58           Mean         Median           15.98         15           35.20         35           0.02         0           0.14         0           0.11         0           Mean         Median           15.98         15           35.20         35           0.02         0           0.14         0           12.99         78           15.24         14.47           34.54         34.635           2.26         2.11           0.48         0	Panel A - Portform           Mean         Median         Deviation           11.86         10         7.41           23.44         21         11.68           3.20         2         2.55           7,235.63         0.00         89,241.34           -0.01         0.00         0.09           0.01         0.01         0.02           46,795.53         964.58         343,661.40           Panel C - 7         Standard           Mean         Median         Deviation           15.98         15         7.99           35.20         35         10.99           0.02         0         0.12           0.11         0         0.32           Standard           Deviation         0.32           15.98         15         7.99           35.20         35         10.91           0.11         0         0.32           0.11         0         0.32           112.99         78         109.15           15.24         14.47         5.66           34.54         34.635         6.82           2.26         2.11 <td< td=""><td>Panel A - Portibio character           Mean         Median         Deviation         Min           11.86         10         7.41         5           23.44         21         11.68         6           3.20         2         2.55         1           7,235.63         0.00         89,241.34         0.00           -0.01         0.00         0.09         -0.56           0.01         0.01         0.02         0.00           46,795.53         964.58         343,661.40         -40,434.86           Fareitaria transfer           Managements           Mean         Median         Deviation         Min           Median         Deviation         Min           Standard           Mean         Median         Deviation         Min           15.98         15         7.99         0         35.20         35         10.99         5           0.02         0         0.12         0         0         0         0           0.11         0         0.32         0         0         0         0         0           112.99         78         &lt;</td><td>Panel A - Portfolio characteristics           Standard         Min         p25           11.86         10         7.41         5         5           23.44         21         11.68         6         15           3.20         2         2.55         1         1           7,235.63         0.00         89,241.34         0.00         0.00           -0.01         0.00         0.09         -0.56         -0.03           0.01         0.01         0.02         0.00         0.01           46,795.53         964.58         343,661.40         -40,434.86         0.00           46,795.53         964.58         343,661.40         -40,434.86         0.00           46,795.53         964.58         343,661.40         -40,434.86         0.00           46,795.53         964.58         343,661.40         -40,434.86         0.00           46,795.53         964.58         343,661.40         -40,434.86         0.00           46,795.53         964.58         343,661.40         -40,434.86         0.00           520         35         10.99         5         27           0.02         0         0         0         0</td><td>Standard           Mean         Median         Deviation         Min         p25         p75           11.86         10         7.41         5         5         15           23.44         21         11.68         6         15         29           3.20         2         2.55         1         1         4           7,235.63         0.00         89,241.34         0.00         0.00         0.00           -0.01         0.00         0.09         -0.56         -0.03         0.03           0.01         0.01         0.02         0.00         0.01         0.01           46,795.53         964.58         343,661.40         -40,434.86         0.00         10,092.81           Terret B - Manager characteristics           Standard           Mean         Median         Deviation         Min         p25         p75           15.98         15         7.99         0         10         20           35.20         35         10.99         5         27         41           0.02         0         0.32         0         0         0           0.12         0&lt;</td><td>Panel A - Portfolio characteristics           Standard           Mean         Median         Deviation         Min         p25         p75         Max           11.86         10         7.41         5         5         15         30           23.44         21         11.68         6         15         29         52           3.20         2         2.55         1         1         4         18           7,235.63         0.00         89,241.34         0.00         0.00         0.00         12,400,000           -0.01         0.00         0.09         -0.56         -0.03         0.03         0.21           0.01         0.01         0.02         0.00         0.01         0.01         1.14           46,795.53         964.58         343,661.40         -40,434.86         0.00         10,092.81         11,700,000           Variation         Min         p25         p75         Max           Standard           Mean         Median         Deviation         Min         p25         p75         Max           15.98         15         7.99         0         10         1</td></td<>	Panel A - Portibio character           Mean         Median         Deviation         Min           11.86         10         7.41         5           23.44         21         11.68         6           3.20         2         2.55         1           7,235.63         0.00         89,241.34         0.00           -0.01         0.00         0.09         -0.56           0.01         0.01         0.02         0.00           46,795.53         964.58         343,661.40         -40,434.86           Fareitaria transfer           Managements           Mean         Median         Deviation         Min           Median         Deviation         Min           Standard           Mean         Median         Deviation         Min           15.98         15         7.99         0         35.20         35         10.99         5           0.02         0         0.12         0         0         0         0           0.11         0         0.32         0         0         0         0         0           112.99         78         <	Panel A - Portfolio characteristics           Standard         Min         p25           11.86         10         7.41         5         5           23.44         21         11.68         6         15           3.20         2         2.55         1         1           7,235.63         0.00         89,241.34         0.00         0.00           -0.01         0.00         0.09         -0.56         -0.03           0.01         0.01         0.02         0.00         0.01           46,795.53         964.58         343,661.40         -40,434.86         0.00           46,795.53         964.58         343,661.40         -40,434.86         0.00           46,795.53         964.58         343,661.40         -40,434.86         0.00           46,795.53         964.58         343,661.40         -40,434.86         0.00           46,795.53         964.58         343,661.40         -40,434.86         0.00           46,795.53         964.58         343,661.40         -40,434.86         0.00           520         35         10.99         5         27           0.02         0         0         0         0	Standard           Mean         Median         Deviation         Min         p25         p75           11.86         10         7.41         5         5         15           23.44         21         11.68         6         15         29           3.20         2         2.55         1         1         4           7,235.63         0.00         89,241.34         0.00         0.00         0.00           -0.01         0.00         0.09         -0.56         -0.03         0.03           0.01         0.01         0.02         0.00         0.01         0.01           46,795.53         964.58         343,661.40         -40,434.86         0.00         10,092.81           Terret B - Manager characteristics           Standard           Mean         Median         Deviation         Min         p25         p75           15.98         15         7.99         0         10         20           35.20         35         10.99         5         27         41           0.02         0         0.32         0         0         0           0.12         0<	Panel A - Portfolio characteristics           Standard           Mean         Median         Deviation         Min         p25         p75         Max           11.86         10         7.41         5         5         15         30           23.44         21         11.68         6         15         29         52           3.20         2         2.55         1         1         4         18           7,235.63         0.00         89,241.34         0.00         0.00         0.00         12,400,000           -0.01         0.00         0.09         -0.56         -0.03         0.03         0.21           0.01         0.01         0.02         0.00         0.01         0.01         1.14           46,795.53         964.58         343,661.40         -40,434.86         0.00         10,092.81         11,700,000           Variation         Min         p25         p75         Max           Standard           Mean         Median         Deviation         Min         p25         p75         Max           15.98         15         7.99         0         10         1		

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**Table 2:** This table displays the results of logistic and OLS regressions with the dependent variable monthly portfolio inflows (OLS), or if there was any inflow (logistic) regressed on positive and negative emotional tone including various control variables. Monthly return, return standard deviation and assets under management are lagged by one month. Standard errors are clustered by portfolio and appear in parentheses. Time fixed effects include both month and year fixed effects. Available investment fixed effects control for available investment vehicles to portfolio managers such as stocks, funds, ETFs, certificates, or derivatives. Style fixed effects control for analysis style such as fundamental, technical, or other types of analyses. Portfolio type fixed effects control for whether the portfolio is labeled as managed by a private manager, an asset management company, a media institution, or an exchange association. Controls for readability include word count, average number of words per sentence, and share of words with more than six letters.

	(1)	(2)	(3)
			OLS incl.
			manager
VARIABLES	Logit	OLS	controls
Pos. Tone	-0.0896**	-0.0455**	-0.0555**
	(0.0428)	(0.0191)	(0.0261)
Neg. Tone	-0.0254	-0.0233	-0.0650*
	(0.0789)	-0.0406	(0.0368)
Fee	-0.0244**	-0.00779	-0.0110*
	(0.00947)	(0.00502)	(0.00640)
Age	0.0514***	-0.00416	-0.00557
	(0.00721)	(0.00429)	(0.00476)
No. of portfolios	0.0349	$0.0278^{*}$	-0.00654
	(0.0250)	(0.0148)	(0.0187)
Pre-emission sd	0.449	6.477***	8.395***
	(3.380)	(2.006)	(2.643)
Pre-emission ret	1.169***	0.997***	1.006***
	(0.349)	(0.165)	(0.237)
Lag month ret	1.496***	4.124***	4.396***
	(0.204)	(0.260)	(0.340)
Lag month sd	23.79***	26.30***	27.04***
-	(2.698)	(2.264)	(2.764)
Lag raw aum	1.88e-05***	2.95e-06***	4.22e-06***
C .	(2.16e-06)	(6.28e-07)	(6.97e-07)
Manager experience			0.0214***
			(0.00525)
Real name [yes=1]			0.182
			(0.140)
Job in finance [yes=1]			-0.00536
			(0.114)
Constant	-2.093**	3.084***	3.398***
	(0.864)	(0.571)	(0.642)
Control for readability	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes
Style fixed effects	Yes	Yes	Yes
Available investments fixed effects	Yes	Yes	Yes
Portfolio type fixed effects			Yes
Observations	55,897	55,897	35,730
R-squared	0.2578	0.167	0.193
No. Cluster	3223	3223	2016

**Table 3:** This table displays the results of OLS regressions of different return and risk measures regressed on positive and negative emotional tone including various control variables. Robust standard errors are clustered by portfolio and appear in parentheses. Time fixed effects include both half year and year fixed effects. Available investment fixed effects control for available investment to portfolio managers such as stocks, funds, ETFs, certificates, or derivatives. Style fixed effects control for investment style such as fundamental, technical, or other types of analyses. Alphas are semi-annualized.

	(1)	(2)	(3)	(6)
VARIABLES	Raw return	Alpha 1	Alpha 3	Risk
Pos. Tone	-0.00298	-0.000267	-0.000795	0.000212
	(0.00280)	(0.00291)	(0.00303)	(0.000141)
Neg. Tone	0.00710*	0.00537*	0.00431	-2.70e-05
	(0.00420)	(0.00287)	(0.00280)	(0.000238)
Fee	-0.00213***	-0.000868	-0.00116*	0.000128***
	(0.000791)	(0.000633)	(0.000649)	(4.75e-05)
No. of portfolios	0.000823	0.00174*	0.00167	0.000179
	(0.00192)	(0.000962)	(0.00118)	(0.000114)
Portfolio age	0.000438	-8.57e-05	4.73e-05	-6.46e-05**
	(0.000643)	(0.000637)	(0.000636)	(3.23e-05)
lagged sem. ann. aum	-0.00251**	-0.000488	-0.000278	6.22e-05
	(0.00112)	(0.00106)	(0.00105)	(5.62e-05)
lagged sem. ann. return				0.00807
				(0.00519)
lagged sem.ann. inflow	0.00317**	0.000962	0.00109	-1.88e-05
	(0.00127)	(0.000901)	(0.000878)	(6.25e-05)
lagged sem.ann. sd	-7.384***	-1.903*	-2.610**	
	(2.101)	(1.040)	(1.160)	
lagged dependent variable	-0.0507	-3.378	-9.756**	0.812***
	(0.101)	(5.615)	(4.266)	(0.125)
Constant	0.165***	0.0199	0.0203	-0.000420
	(0.0411)	(0.0325)	(0.0332)	(0.00198)
Control for readability	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes
Style fixed effects	Yes	Yes	Yes	Yes
Available investments fixed effects	Yes	Yes	Yes	Yes
Observations	3,196	3,197	3,197	3,196
R-squared	0.189	0.026	0.038	0.411

**Table 4:** LIWC results of the experimental induction in study 2. We adapted four prototypes from original self-descriptions and equipped them with either positive emotion words or negative emotion words. As a baseline, we implemented two control conditions.

	WC	WPS	Sixltr	Posemo	Negemo
Control 1.1	43	8.60	27.91	2.33	0.00
Control 1.2	38	9.50	21.05	0.00	0.00
Control 1.3	44	11.00	45.45	2.27	0.00
Control 1.4	61	8.71	34.43	0.00	0.00
Control 2.1	49	12.25	26.53	2.04	0.00
Control 2.2	55	13.75	18.18	0.00	0.00
Control 2.3	43	14.33	48.84	4.65	0.00
Control 2.4	71	10.14	35.21	0.00	0.00
Positive 1	50	10.00	24.00	6.00	0.00
Positive 2	46	11.50	23.91	6.52	0.00
Positive 3	53	13.25	35.85	9.43	0.00
Positive 4	68	9.71	33.82	5.88	1.47
Negative 1	52	10.40	25.00	1.92	7.69
Negative 2	51	12.75	23.53	0.00	3.92
Negative 3	58	14.50	37.93	1.72	5.17
Negative 4	77	11.00	31.17	0.00	6.49

**Table 5:** Experimental data regression analyses. OLS regressions including self-description (prototype) and participant fixed effects to control for content-wise differences of self-descriptions and individual differences in preferences (Results remain unchanged if we use ordinal probit regressions). Columns (1) and (2) report on the effect of word use (positive emotion and negative emotion) on the willingness to copy the portfolio managers' investments and on the percentage share of investments. Columns (3) and (4) report the results on participants' perception on portfolio managers' intent and competence as a result of word use (positive emotion and negative emotion). Colums (5) and (6) report the results on the effects of intent and competence mediating the relationship between word use and investments.

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	invest	%invest	intent	competence	invest	%invest
Pos. Tone	-0.0884***	-0.965***	0.00783	-0.0472***	-0.0372***	-0.384
	(0.0191)	(0.329)	(0.00975)	(0.0108)	(0.0141)	(0.307)
Neg. Tone	0.00621	0.551	0.0381***	0.00162	-0.00504	0.358
	(0.0195)	(0.395)	(0.00994)	(0.0110)	(0.0142)	(0.363)
Intent					0.247***	4.505***
					(0.0646)	(1.387)
Competence					1.125***	13.06***
					(0.0586)	(1.383)
Prototype 2	-0.114	-2.080	-0.0993	-0.0373	-0.0475	-0.0699
	(0.125)	(2.244)	(0.0637)	(0.0703)	(0.0901)	(0.0751)
Prototype 3	0.0479	-3.231	0.239***	0.0265	-0.0411	-0.169**
	(0.125)	(2.163)	(0.0638)	(0.0704)	(0.0913)	(0.0763)
Prototype 4	0.281**	2.627	-0.0802	0.336***	-0.0771	0.00867
	(0.123)	(2.405)	(0.0627)	(0.0692)	(0.0913)	(0.0748)
Constant	4.336***	27.49***	-0.0955	0.0470	4.306***	27.31***
	(0.115)	(1.697)	(0.0584)	(0.0644)	(0.0828)	(1.553)
Participant FE	YES	YES	YES	YES	YES	YES
Observations	784	784	784	784	784	784
R-squared	0.067	0.048	0.085	0.103	0.519	0.252
Number of id	196	196	196	196	196	196

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# Appendix

# **Example of manager self-descriptions:**

I invest in German stocks since 1986 and in worldwide stocks and derivatives since the 90s. During this time period my portfolio outperformed the DAX even after transaction costs. Being a safety-oriented investor I built my system so that losses in crises are relatively small and accept limitations in profits during boom markets. I see \*\*\* certificates as an excellent opportunity to implement my trading strategy: [...]

# Common positive and negative words in manager self-descriptions:

Positive words:



# Negative words:



# Experimental self-description prototypes:

Prototype	pe Control 1		Control 2		Positiv	ve Tone	Negative Tone	
1	Ich handle seit 1998 mit Aktien und habe schon viel Erfahrungen gesammelt. Die perfekte Anlagelösung hängt immer auch vom Bauchgefühl ab. Ich beschäftige mich vor allem mit mittel- bis langfristigen Anlagen. Hier konnte ich bisher eine durchschnittliche jährliche Rendite von ca. 20% erwirtschaften.	I've been trading stocks since 1998 and I've already collected a lot of experience. The perfect investment strategy always also depends on your gut feelings. I'm nainly interested in intermediate- and long-term investments. By this, I could make an avergage yearly return of 20% so far.	Weil ich schon seit 1998 mit Aktien handle, habe ich schon viele Erfahrungen gesammelt. Dadurch weiß ich: Die perfekte Anlagelösung hängt immer auch vom Bauchgefühl ab. Ich beschäftige mich vor allem mit mittel- bis langfristigen Anlagen, denn so konnte ich bisher eine durchschnittliche jährliche Rendite von ca. 20% erwirtschaften.	Because I've been trading stocks since 1998, I've already collected a lot of experience. That's why I know: The perfect investment strategy always also depends on your gut feelings. I'm mainly interested in intermediate- and long-term investments, because by this, I could make an averqage yearly return of 20% so far.	Ich handle seit 1998 mit Aktien und habe schon viele tolle Erfahrungen gesammelt. Die perfekte Anlagelösung geht bei nir immer mit gutem Bauchgefühl einher. Ich lege mit Leidenschaft vor allem in mittel- bis langfrästige Anlagen an. Hier konnte ich bisher eine sehr gute durchschnittliche jährliche Rendite von ca. 20%	Ive been trading stocks since 1998 and Ive already collected a lot of great experiences. The perfect investment strategy always goes along with good gut feelings. Im passionate about investing, mainly in intermediate- and long-term investments. By this, I could make a very good avergage yearly return of 20% so far.	Ich handle seit 1998 mit Aktien und weiß auch, wann es schief gehen kann. Die perfekte Anlagelösung wird bei mir nie mit schlechtem Bauchgefühl getroffen. Ich vermeide Angst und Gier und beschäftige mich vor allem mit mittel- bis langfristigen Anlagen. Hier konnte ich bisher eine durchschnittliche jährliche Rendite von ca. 20% erwirtschaften.	I've been trading stocks since 1998 and I know, when things can go wrong. The perfect investment strategy never goes along with bad gut feelings. I avoid fear and greed and mainly interest in intermediate- and long- term investments. By this, I could make an averqage yearly return of 20% so far.
2	Ich bin ehemaliger BWL-Student mit Vertiefung in Banking. Ich handle seit 10 Jahren mit Aktien und habe schon alles erlebt. Ich lege Wert auf Diversifikation und am Ende zählt das Ergebnis. Ich habe meine eigene Strategie entwickelt.	I'm a former business student with focus on banking. I've been trading for 10 years with stocks and I've already seen everything. I value diversification and in the end it is the result that counts. I've developed my own strategy.	Ich bin ehemaliger BWL-Student mit Vertiefung in Banking. Durch mein Studium und weil ich schon seit 10 Jahren mit Aktien handle, habe ich schon alles erlebt. Aus diesem Grund lege ich besonders viel Wert auf Diversifikation, denn am Ende zählt das Ergebnis. Da ich meine eigene Strategie entwickelt habe, weiß ich, was ich tue.	I'm a former business student with focus on banking. Due to my studies and because I've been trading for 10 years with stocks, I've already seen everything. That's why I especially value diversification, because in the end it is the result that counts. Because I've developed my own strategy, I know what I'm doing.	Ich bin ehemaliger BWL-Student mit Vertiefung in Banking. Ich handle seit 10 Jahren erfolgreich mit Aktien und habe schon viel Schönes erlebt. Ich lege Wert auf Diversifikation und am Ende zählen die Gewinne. Ich habe meine eigene Strategie entwickelt, mit der ich sehr zufrieden bin.	I'm a former business student with focus on banking. I've been successfully trading for 10 years with stocks and I've already experienced a lot of good things I value diversification and in the end it is the gains that count. I've developed my own satisfying strategy.	Ich bin ehemaliger BWL-Student mit Vertiefung in Banking. Ich handle seit 10 Jahren mit Aktien und habe schon alles erlebt, auch dass es schmerzen kann. Ich lege Wert auf Diversifikation und am Ende zählt das Ergebnis. Ich habe meine eigene Strategie entwickelt, mit der ich selbst schlechten Marktentwicklungen entgegnen kann.	I'm a former business student with focus on banking. I've been trading for 10 years with stocks and I've already seen everything, also that trading can hurt. I value diversification and in the end it is the result that counts. I've developed my own strategy that allows me to deal with poor market developments.
3	Ich habe mein Studium der Betriebswirtschaftslehre sowie eine Lehre zum Bankkaufmann abgeschlossen und habe schon einige Jahre Erfahrung am Kapitalmarkt gesammelt. Wertpapier-Trading betreibe ich als nebenberufliche Beschäftigung. Bewusstes Handeln steht für mich im Vordergrund. Nun verfolge ich eine Strategie, die konstante Renditen einbringt.	I finished my studies of business administration as well as my education to be a qualified banker and I've already collected several years of experiences in capital markets. I do security trading as a side job. Conscientious behavior is my priority. I'm now folling a strategy that leads to constant returns.	Durch mein Studium der Betriebs wirtschaftslehre sowie eine abgeschlossene Lehre zum Bankkaufmann, habe ich schon einige Jahre Erfahrungen am Kapitalmarkt gesammelt. Dadurch kann ich Wertpapier- Trading als nebenberufliche Beschäftigung betreiben. Da ich bewusstes Handeln wichtig finde, verfolge ich eine Strategie, die konstante Renditen erzielt.	Due to my I my studies of business administration as well as my education to be a qualified banker, I've ahready collected several years of experiences in capital markets. That's why I can do security trading as a side job. Because conscientious behavior is my priority. I'm folling a strategy that leads to constant returns.	Ich habe mein Studium der Betriebswirtschaftslehre sowie eine super spannende Lehre zum Bankkaufmann abgeschlossen und schon einige Jahre tolle Erfahrungen am Kapitalmarkt gesammelt. Wertpapier-Trading betreibe ich als Hobby und bin mit Freude und Leidenschaft dabei! Bewusstes Handeln steht für mich im Vordergrund. Nun verfolge ich eine super Strategie, die schöne Renditen einbringt.	I finished my studies of business administration as well as a very exciting education to be a qualified banker and I've already collected several years of great experiences in capital markets. Security trading is my hobby and I'm into it with pleasure and passion. Conscientious behavior is my priority. I'm now folling a great strategy that leads to nice returns.	Betriebs wirtschaftslehre sowie eine Lehre zum Bankkaufmann abgeschlossen und habe schon einige, auch schmerzhafte, Jahre Erfahrungen am Kapitalmarkt gesammelt. Wertpapier-Trading betreibe ich als Hobby und ich bin mit Adrenalin, Angst und Leidenschaft dabei. Bewusstes Handeln steht für mich im Vordergrund. Nun verfolge ich eine Strategie, die konstante Renditen einbringt ohne mich zu stressen.	I finished my studies of business administration as well as my education to be a qualified banker and Ive already collected several years of, also hurting, experiences in capital markets. Security trading is my hobby and Im into it with adrenaline, fear and passion. Conscientious behavior is my priority. Im now folling a strategy that leads to constant retums without stressing me out.
4	Ich bin ein 45-jähriger Börsianer. Ich war schon immer zahlenaffin und habe Wirtschaftswissenschaften studiert. Während meines Studiums habe ich begonnen, mich mit den Geschchnissen am Kapitalmarkt zu beschäftigen. Mein Wissen und meine Intuition halfen mir von Anfang an beim Trading. Auch während der Finanzkrise erzielte ich mithilfe von Shortpositionen meine Renditen. Ich wende täglich ca. 251d für meine Handelsidee auf.	I am a 45 year old stock exchange speculator. I've always been keen on numbers and I studied economics. During my studies I started to be interested in capital market events. My knowledge and my intution helped me from the very beginning while trading. Even throughout the financial crisis I was able to reach my returns with shorting. I spend approximately 2 hours daily on trading.	Ich bin ein 45-Jähriger Börsianer. Ich war schon immer zahlenafin, weshalb ich dann auch Wirtschafts wissenschaften studiur habe. Durch mein Studium habe ich begonnen, mich mit den Geschehnissen am Kapitalmarkt zu beschäftigen. Durch mein Wissen und meine Intuition habe ich verläss siche Helfer beim Trading. Weil ich zu Beginn der Finanzkrise diverse Shortpositionen hielt, konnte ich weiterhin meine Renditen erzielen. Wahrscheinlich auch dadurch, dass ich täglich ca. 2Sid für meine Handelsidee aufwende.	I am a 45 year old stock exchange speculator. I've always been keen on numbers, which is why I studied economics. Because of my studies I started to be interested in capital market events. Due to my knowledge and my intution I have reliable help while trading. Because I was holding several short positions at the beginning of the financial crisis, I was able to reach my returms. Probalby also because I spend approximately 2 hours daily on trading.	Ich bin ein 45-jähriger, glücklicher Börsianer. Ich mag Zahlen sehr gem und habe Wirtschafts wissenschaften studiert. Während meines spannenden Studiums habe ich begonnen, mich mit den aufregenden Geschehnissen am Kapitalmarkt zu beschäftigen. Mein Wissen und meine gute Intuition sind mir tolle Helfer beim Trading. Zu Beginn der Finanzkrise hielt ich diverse Shortpositionen und erzielte so weiterhin gute Renditen. Ich wende täglich ca. 2 Std für meine Handelsidee auf.	I am a 45 year old happy stock exchange speculator. I really like numbers numbers and I studied economics. During my exciting studies I started to be interested in capital market events. My knowledge and my good intution helped me from the very beginning while trading. Even throughout the financial crisis I was able to keep on having good returns with shorting. I spend approximately 2 hours daily on trading.	Ich bin ein 45-jähriger Börsianer. Ich war Zahlen nie abgeneigt und habe Wirtschaftswissenschaften studiert. Während meines eher langweiligen Studiums habe ich begonnen, mich mit den turbulenten Geschehnissen am Kapitalmarkt zu beschäftigen. Mein Wissen und meine Intuition halffen in Krisenzeiten die Nerven zu behalten. Zu Beginn der Finanzkrise hielt ich diverse Shortpositionen und vermied so, dass der Schaden für mich nicht zu groß war, eher im Gegenteil. Ich wende täglich ca. 2 Std für meine Handelsidee auf.	I am a 45 year old stock exchange speculator. I've never been reluctant to numbers and I studied economics. During my rather boring studies I started to be interested in the turbulent capital market events. My knowledge and my intution helped me to keep my nerves throughout times of crisis. Even throughout times of crisis. Even throughout times of crisis. Even throughout times of crisis such as a such as the to avoid too big losses with shorting, rather the opposite was the case. I spend approximately 2 hours daily on trading.