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Overconfidence and Trading Volume

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October 28, 2005

Abstract

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Keywords: Overconfidence, Differences of Opinion, Trading Volume, Individual Investors, Investor Behavior, Correlation of Economic and Psychological Variables, Combination of Psychometric Measures of Judgment Biases and Field Data

JEL Classification Code: D8, G1

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1 Introduction

Trading volume appears high in financial markets. One quarter of the value of the annual worldwide trade and investment flow is traded in the foreign exchange market (including forwards, swaps, and spot transactions) *each day*.[1] The annualized monthly turnover on the New York Stock Exchange (NYSE) in the last years was about 100 %. The number of shares traded on the NYSE in the year 2004 was 367,098,489,000 and the daily value of trading is currently about 55 billion.[2] De Bondt and Thaler (1995) note that the high trading volume observed in financial markets "is perhaps the single most embarrassing fact to the standard finance paradigm".[3]

Why do investors trade such enormous quantities? Rational investors must be heterogeneous for trade to be mutually advantageous for the buyer and the seller of an asset. Differences in information alone cannot explain high levels of trading volume. This is a result of various no trade theorems, among them, for example, Milgrom and Stokey (1982).[4]

Introduction of noise traders or liquidity traders who trade for reasons exogenous to models helps to circumvent no trade theorems.[5] This noise or liquidity trading is not necessarily irrational. For example, endowment shocks, such as bequests or accidents, can be interpreted as liquidity trading motives.[6] But common sense suggests that ascribing the high levels of trading volume mentioned above solely to noise or liquidity trading is unsatisfying.[7]

Two further strands of literature have emerged that are able to explain high levels of trading volume. These strands of literature are labeled as the "differences of opinion"

[1] Dow and Gorton (1997), p. 1026.

[2] See www.nyse.com.

[3] De Bondt and Thaler (1995), p. 392.

[4] See, for example, Brunnermeier (2001), pp. 30-37, for a discussion of various no trade theorems.

[5] See Pagano and Röell (1992), p. 680, and Brunnermeier (2001), p. 31. Shleifer and Summers (1990) survey the noise trader approach to finance.

[6] See, for example, Pagano and Röell (1992), p. 680.

[7] See also Hirshleifer (2001), p. 1564, and Wang (1998), p. 322.

literature and the “overconfidence” literature.[8] We now shortly discuss these two strands of literature in turn. A more comprehensive discussion will follow in Subsection 3.2.

The “differences of opinion” literature was, among others, motivated by Varian (1985, 1989). Differences of opinion can arise due to differences in prior beliefs or due to differences in the way investors interpret public information. Furthermore, it is assumed that these differences in beliefs or models for interpreting signals are common knowledge. Although everyone knows that others have different opinions, there is no adjustment of beliefs, i.e. investors “agree to disagree”. Modeling differences of opinion is mainly motivated by mere plausibility: differences of opinion are present in every day life (see, for example, Harris and Raviv (1993)). The models are usually silent about the reason why there are differences of opinion in the first place. Varian (1989), Harris and Raviv (1993), and Kandel and Person (1995) show that differences of opinion help explain high levels of trading volume and that a higher degree of differences of opinion leads to a higher degree of trading volume.

The “overconfidence” literature assumes that investors overestimate the precision of information. Overconfidence models thus incorporate findings of a large set of psychological studies that are often referred to as the “calibration literature” (see, for example, Lichtenstein, Fischhoff, and Phillips (1982)). However, overconfidence models are usually motivated by a richer set of psychological results that are often summarized as overconfidence.[9] These theoretical models predict that overconfident investors trade more than rational investors. De Bondt and Thaler (1995) argue that “the key behavioral factor needed to understand the trading puzzle is overconfidence”.[10]

The discussion so far raises the following questions that our study will tackle empirically:

1. Is trading volume of an investor a function of the degree of miscalibration of the respective investor as claimed by the “overconfidence” literature?
2. Is the trading volume of an investor a function of other overconfidence measures that are often used as a motivation of overconfidence models?

[8]Morris (1994) shows that even in a “differences of opinion” setting no trade theorems can arise under certain conditions.

[9]We will discuss these further results in Subsection 3.1.

[10]De Bondt and Thaler (1995), p. 393.

3. Are the various overconfidence measures used to motivate overconfidence models positively correlated?
4. Is there a psychological foundation of the "differences of opinion" explanation of high levels of trading volume?

We analyze these questions by correlating various overconfidence measures with measures of trading volume. A sample of approximately 3,000 individual investors with online broker accounts was asked to answer an online questionnaire which was designed to measure various facets of overconfidence, among them their degree of miscalibration. For the subgroup of 215 respondents we are able to correlate overconfidence measures and measures of trading volume which are calculated by the trades over a 51 month period.

By correlating miscalibration scores with measures of trading volume we are able to empirically test the hypothesis of overconfidence models that, the higher the degree of miscalibration (modeled as the degree of the overestimation of the precision of information), the higher the trading volume of the respective investor. In addition, we explore whether other biases which are often summarized as overconfidence and are used to motivate overconfidence models are related to trading volume. Such an analysis is necessary to guide modeling. Psychologists have found several judgment biases but it remains unclear which bias affects economic behavior or whether these biases affect economic behavior at all. These points are often put forth as a major drawback of behavioral finance models. In this vein, Fama (1998) argues that "given the demonstrated ingenuity of the theory branch of finance, and given the long litany of apparent judgment biases unearthed by cognitive psychologists, it is safe to predict that we will soon see a menu of behavioral models that can be mixed and matched to explain specific anomalies."[11] This statement shows the importance of analyzing the link or correlation between judgment biases and economic variables such as trading volume as the only way to test which bias actually influences economic behavior. Our paper is among the few recent papers that measures psychological biases and correlates them with economic choices. Other recent examples are Graham, Harvey, and Huang (2005) or Puri and Robinson (2005).

Furthermore, we are able to test whether there is a psychological foundation of differences

[11] Fama (1998), p. 291.

of opinion models by explicitly asking investors whether they assess themselves as above average with regard to investment skills or past performance. We argue that an investor who regards himself as above average is more likely to maintain a specific opinion about the future performance of an asset even though he knows that other investors or the market hold a different opinion. Note, that this difference of opinion is the source of volume in the “differences of opinion” literature. By correlating measures of trading volume with miscalibration scores and better than average scores, we are able to empirically evaluate whether the “differences of opinion” literature or the “overconfidence” literature better explains high levels of trading volume.

Our main findings can be summarized as follows. Investors who think that they are above average trade more. This finding is consistent with other recent studies (see Deaves, Lüders, and Luo (2003), Graham, Harvey, and Huang (2005), Hales (2005), Oberlechner and Osler (2003)). Measures of miscalibration are, contrary to predictions of overconfidence models, unrelated to measures of trading volume. These results hold even when we control for several other explanatory variables in a cross-sectional regression analysis. In connection with other recent findings, we conclude that the usual way of motivating and modeling overconfidence which is based on the calibration literature has to be treated with caution. In line with other authors, we argue that the “differences of opinion” literature better explains high levels of trading volume when compared to the “overconfidence” literature. Furthermore, our findings are consistent with a psychological foundation for the “differences of opinion” explanation of high levels of trading volume. In addition, our way of empirically evaluating behavioral finance models - the correlation of economic and psychological variables and the combination of psychometric measures of judgment biases (such as overconfidence scores) and field data - seems to be a promising way to better understand which psychological phenomena drive economic behavior.

The rest of the paper is organized as follows. Section 2 surveys related research, especially other endeavors to test our main hypothesis and their drawbacks. Section 3 surveys overconfidence in the literature on heuristics and biases and in the finance literature. Section 4 describes the data set and the design of our study, especially our overconfidence measures. Section 5 shows the results on the relation between measures of overconfidence and trading volume and presents several robustness checks and alternative interpretations of our results. Section 6 discusses the results and the last section concludes.

2 Related Research

Our analysis is related to other studies which share the common feature of correlating proxies or measures of overconfidence on the one hand and economic variables such as trading volume on the other hand.

Statman, Thorley, and Vorkink (2004) use U.S. market level data to test the hypothesis that overconfidence leads to high trading volume. They argue that after high returns subsequent trading volume will be higher as investment success increases the degree of overconfidence.[12] They find an increase in trading activity after bull markets: stock trading volume (turnover) is positively related to lagged stock returns. This finding is consistent with the hypothesis that a higher degree of overconfidence leads to higher trading volume as long as high past returns are a proxy for overconfidence. Kim and Nofsinger (2003) confirm these findings using Japanese market level data. They identify stocks with varying degrees of individual ownership to test the hypothesis and discover higher monthly turnover in stocks held by individual investors during the bull market in Japan.

The proxy for overconfidence in Barber and Odean (2001) is gender. In their paper, they summarize psychological studies that find a higher degree of overconfidence among men than among women. Consequently, they partition their data set, a sample of U.S. online broker investors, on gender. They find that men trade more than women which is consistent with overconfidence models.

All the above mentioned studies share the shortcoming that overconfidence is never directly observed. Only crude proxies for overconfidence are used (past returns, gender). A direct test of the hypothesis that a higher degree of overconfidence leads to higher trading volume is the correlation of measures of overconfidence and measures of trading volume. Our study uses this approach. Our research is thus related to the studies in economics and finance that correlate psychological data (such as measures of overconfidence) with economic variables (such as trading volume). We will discuss such studies in the rest of

[12] See Subsection 5.3 for a further discussion of dynamic overconfidence models.

this subsection.

Fenton-O'Creevy, Nicholson, Soane, and Willman (2003) analyze the link between psychological and economic variables empirically using data on the behavior of professional traders. They measure illusion of control (Langer (1975), Presson and Benassi (1996)) by a computer-based task. They find that their measure of illusion of control is negatively associated with performance as measured by traders' self-ratings, total annual earnings, and the performance assessments of a senior trader-manager.[13]

Biais, Hilton, Mazurier, and Pouget (2005) analyze experimentally whether psychological traits and cognitive biases affect trading and performance. Based on the answers of 245 subjects (students) to a psychological questionnaire they measured, among other psychological traits, the degree of overconfidence via calibration tasks. The subjects also participated in an experimental asset market. They find that overconfidence (miscalibration) reduces trading performance in the experimental asset market. However, their overconfidence measure is unrelated to trading volume. Contrary to predictions of overconfidence models, overconfident subjects do not place more orders.

Using data from several UBS/Gallup Investor Surveys, Graham, Harvey, and Huang (2005) measure investor competence through survey responses. They find that investors who feel competent trade more often and have a more internationally diversified portfolio.

Puri and Robinson (2005) link optimism to major economic choices. They create a measure of optimism using the Survey of Consumer Finance by comparing a person's self-reported life expectancy to that implied by statistical tables. Optimists are more likely to believe that future economic conditions will improve. In addition, they tilt their investment portfolios more toward individual stocks.

[13]There is another study (Dorn and Huberman (2002)) which analyzes, among other things, the link between psychological variables (overconfidence) and economic variables (portfolio turnover) empirically using a transaction data set of online broker investors which is similar to ours. They measure overconfidence via a questionnaire as the difference between perceived and actual financial market knowledge and a self-attribution bias score. Their finding is that these overconfidence measures fail to explain additional variation in trading volume (p. 33). The overconfidence measures in Dorn and Huberman (2002) are, however, not based on the original psychological overconfidence studies, a point which they themselves acknowledge as they conclude in their paper that one should "conduct experimental tests of overconfidence and compare the results with actual trading behavior" (p. 34).

3 Overconfidence as a Judgment Bias and in Finance Models

3.1 Overconfidence as a Judgment Bias

In the literature on heuristics and biases there is no precise definition of overconfidence. There are several findings that are often summarized as overconfidence. Under this view, overconfidence can manifest itself in the following forms: miscalibration, too tight volatility estimates, and the better than average effect.[14] We will discuss these manifestations of overconfidence in turn.

3.1.1 Miscalibration

Studies that analyze assessments of uncertain quantities using the fractile method usually find that people's probability distributions are too tight (Lichtenstein, Fischhoff, and Phillips (1982)). For example, studies that ask people to state a 90 percent confidence interval for several uncertain quantities find that the percentage of surprises, i.e. the percentage of true values that fall outside the confidence interval, are higher than 10 percent, the percentage of surprises of a perfectly calibrated person. Other studies analyze the calibration of probability judgments. People are asked to answer questions with two answer alternatives. After that, they are asked to state the probability that their answer is correct. The usual finding is that for all questions assigned a given probability the proportion of correct answers is lower than the assigned probability (Lichtenstein, Fischhoff, and Phillips (1982)). There is still a debate in the psychological literature over whether miscalibration is domain or task dependent or even a statistical illusion (see, for example, Gigerenzer, Hoffrage, and Kleinbölting (1991), Klayman, Soll, Gonzáles-Vallejo, and Barlas (1999), Juslin, Winman, and Olson (2000), Erev, Wallsten, and Budescu (1994)). However, the result that people form probability distributions over uncertain quantities that are too tight seems to be robust especially when people judge difficult items (see Klayman, Soll, Gonzáles-Vallejo, and Barlas (1999) or Soll and Klayman (2004)).

[14] Griffin and Brenner (2004), for example, argue that these concepts are linked. They present theoretical perspectives on (mis)calibration, among them the most influential perspective, optimistic overconfidence. According to the authors, the optimistic overconfidence perspective builds, for example, on the better than average effect, unrealistic optimism, and illusion of control.

3.1.2 Volatility estimates

There are several questionnaire studies that elicit the volatility estimate of investors by asking for confidence intervals for the return or value of an index or the return or price of a stock in the future. These studies usually find that the intervals provided are too tight. Thus, historical volatilities are underestimated (see, for example, Glaser, Nöth, and Weber (2004) and Hilton (2001)). The finding that confidence intervals for uncertain quantities are too tight is usually called "miscalibration" or "overconfidence" (see the subsection above). One example is the study of Graham and Harvey (2003) which analyzes expectations of risk premia, as well as their volatility and asymmetry in a panel survey. On a quarterly basis, Chief Financial Officers (CFOs) of U.S. corporations are asked to provide their estimates of the market risk premium. They find that historical volatilities are underestimated. De Bondt (1998) presents results from a study of 46 individual investors. These investors made repeated weekly forecasts of the Dow Jones Industrial Average and of the share price of one of their main equity holdings. For 20 weeks, subjects were asked to provide point forecasts as well as interval estimates for the value or price two or four weeks later. One important finding is that the confidence intervals are too narrow compared to the actual variability of prices. Similar results are obtained by Glaser, Langer, and Weber (2005) for students and professional stock traders.

3.1.3 Better than average effect

People think that they are above average. Taylor and Brown (1988) document in their survey that people have unrealistically positive views of the self. One important manifestation is that people judge themselves as better than others with regard to skills or positive personality attributes. One of the most cited examples states that 82 % of a group of students rank themselves among the 30 percent of drivers with the highest driving safety (Svenson (1981)).

3.2 Overconfidence in Finance Models

In this subsection, we will discuss the "differences of opinion" literature and the "overconfidence'" literature more comprehensively. Investors are willing to trade if their posterior beliefs about the value of a risky asset are different. Theoretically, there are several ways to "create" differing posterior beliefs.[15]

The "differences of opinion" literature was, among others, motivated by Varian (1985, 1989). Varian (1989) generalizes the mean-variance framework with diverse information of Grossman (1976) to allow for different prior probabilities. Each investor has a subjective prior distribution for the value of the risky asset. It is assumed that these prior distributions are normal but have different means. Varian (1989) finds that trading volume is entirely driven by differences of opinion. The equilibrium net trading volume of an investor only depends on the deviation of his opinion about the mean from the average opinion: The larger the differences of opinion, the larger trading volume. Harris and Raviv (1993) assume that investors have common prior beliefs and receive public information. Differences of opinion are modeled by investors interpreting this information differently, i.e. they have different likelihood functions when updating probabilities. Besides assuming differing prior beliefs, Kandel and Person (1995) model differences of opinion as follows. Investors receive a public signal which is the sum of two random variables: the liquidation value of the risky asset plus a random error term. Agents disagree about the mean of the error term. Harris and Raviv (1993) and Kandel and Person (1995) show that their respective model assumptions help explain high trading volume. Most "differences of opinion" models are silent about the reason why there are such differences of opinion. Morris (1995) and van den Steen (2001)) argue that differing prior beliefs are in line with rationality. Shiller (1999), Barberis and Thaler (2003), Hong and Stein (2003), and Diether, Malloy, and Scherbina (2002) regard differences of opinion as a form of overconfidence: investors think that their knowledge or their abilities to value stocks are better than those of other investors.[16]

[15] Varian (1989), p. 6., stresses that different probability beliefs may be due to differences in information or differences in opinion. The distinction between information and opinion depends on how people modify their views when they discover that other people hold different views.

[16] See also Odean (1998b), who argues that overconfidence in one's information is not the only manifestation of overconfidence one might expect to find in markets. He argues that traders could, instead, be overconfident about the way they

In the remainder of this subsection, we focus on overconfidence models that help explain high levels of trading volume. Although motivated by *all* of its manifestations discussed in Subsection 3.1, overconfidence is *exclusively* modeled as overestimation of the precision of private information. Assume there is a risky asset with liquidation value v which is a realization of $\tilde{v} \sim N(0, \sigma_{\tilde{v}}^2)$. Investors receive private signals $\tilde{s} = \tilde{v} + c \cdot \tilde{e}$ with $\tilde{e} \sim N(0, \sigma_{\tilde{e}}^2)$. It is assumed that $\tilde{v}$ and $\tilde{e}$ are independent such that $\tilde{s} \sim N(0, \sigma_{\tilde{v}}^2 + c^2 \cdot \sigma_{\tilde{e}}^2)$. If $c = 1$, investors are rational, if $0 \leq c < 1$, investors are overconfident. Conditional expectation and conditional variance of $\tilde{v}$, given the realization s are (assuming that $\tilde{v}$ and $\tilde{e}$ are independent)

$$E[\tilde{v} \mid \tilde{s} = s] = E[\tilde{v}] + \frac{Cov[\tilde{v}, \tilde{s}]}{Var[\tilde{s}]}(s - E[\tilde{s}]) = \frac{\sigma_{\tilde{v}}^2}{\sigma_{\tilde{v}}^2 + c^2 \cdot \sigma_{\tilde{e}}^2} \cdot s \tag{1}$$

$$Var[\tilde{v} \mid \tilde{s} = s] = Var(\tilde{v}) - \frac{(Cov[\tilde{v}, \tilde{s}])^2}{Var[\tilde{s}]} = \sigma_{\tilde{v}}^2 - \frac{\sigma_{\tilde{v}}^4}{\sigma_{\tilde{v}}^2 + c^2 \cdot \sigma_{\tilde{e}}^2} \tag{2}$$

Overconfident investors underestimate the variance of the risky asset or overestimate its precision. Stated equivalently, their confidence intervals for the value of the risky asset are too tight. In the extreme case ($c = 0$), an investor even believes that he knows the value of the risky asset with certainty. Benos (1998), Caballé and Sákovics (2003), Kyle and Wang (1997), Odean (1998b), and Wang (1998) incorporate this way of modeling overconfidence in different types of models such as those of Diamond and Verrecchia (1981), Hellwig (1980), Grossman and Stiglitz (1980), Kyle (1985), and Kyle (1989).[17] These models differ in various dimensions. Some models assume that price takers are overconfident. Others assume that informed insiders are overconfident and act strategically because they know that they may influence the market price. Some models are one-period models, others study multiple trading rounds. However, all the above mentioned models predict that overconfidence leads to high trading volume. At the individual level, overconfident

interpret public information rather than about the information itself. Furthermore, he emphasizes that each investor is (over)confident in the way she interprets the information even though she "is aware of the beliefs, and perhaps even the signals" of other investors (Odean (1998b), p. 1895).

[17] There are other overconfidence models that address questions like the dynamics of overconfidence, the survival of overconfident investors in markets, and the cross-section of expected returns. Examples are Daniel, Hirshleifer, and Subrahmanyam (1998), Daniel, Hirshleifer, and Subrahmanyam (2001), Hirshleifer and Luo (2001), Gervais and Odean (2001), and Wang (2001).

investors will trade more aggressively: The higher the degree of overconfidence of an investor, the higher her or his trading volume. Odean (1998b) calls this finding "the most robust effect of overconfidence".

Throughout the paper, we maintain the two terms "differences of opinion" literature and "overconfidence" literature. However, differences of opinion are sometimes interpreted as a form of overconfidence, and overconfidence models assume overestimation of the precision of information, which create heterogeneous (posterior) beliefs as well or make the *additional* assumption of differing beliefs that are common knowledge. Nevertheless, the two strands of literature are usually regarded as distinct: The "differences of opinion" literature is usually not regarded as a part of the behavioral finance literature although differences of opinion are sometimes regarded as a form of overconfidence, as described above.[18]

4 Data Sets, Design of the Study, and Overconfidence Measures

The first two subsections of this section describe the various data sets we use and the design of our study. Subsection 4.3 is concerned with a possible selection bias as only 215 of approximately 3,000 investors have responded to the questionnaire. The last subsection describes the questionnaire and the various overconfidence scores we calculated using the answers of the investors.

4.1 Data Sets

This study is based on the combination of several data sets. The main data set consists of 563,104 buy and sell transactions of 3,079 individual investors from a German online broker in the period from January 1997 to April 2001. We considered all investors who trade via the internet, had opened their account prior to January 1997, had at least

[18]The following examples highlight this point. Odean (1998b) argues that his model which assumes miscalibrated investors is, *in contrast to* Harris and Raviv (1993), grounded in psychological research (Odean (1998b), p. 1891). Varian (1989) admits that "differences of opinion ... can be viewed as allowing for a certain kind of irrational behavior" but "remains agnostic on this issue" as his results (trading volume is entirely driven by differences of opinion) do not hinge on "whether we want to call this "rational" or "irrational" " (Varian (1989), p. 7).

one transaction in 1997, and have an e-mail-address.[19] The second data set consists of several demographic and other self-reported information (age, gender, income, investment strategy, investment experience), that was collected by the online broker at the time each investor opened her or his account.[20] The third data set consists of the answers to an online questionnaire that was designed to elicit several measures of overconfidence (see Subsection 4.4). Data on the securities traded are obtained from Datastream, our fourth data source.

4.2 Design of the Study

All 3,079 investors received an e-mail from the online broker on Thursday, August, 2nd, 2001 with a link to the online questionnaire. 129 investors answered around the following week-end. The remaining group of investors received a second e-mail on Thursday, the 20th of September, 2001. 86 investors answered around the following weekend. So, we have a response rate of 6.98 %, which is comparable to the response rates of similar questionnaires.[21]

In this study, we use the following measures of trading volume which are calculated by the trades of the investors: the number of stock market transactions, the number of stock market purchases, and the mean monthly stock portfolio turnover over the period from January 1997 to April 2001. We focus on stock market transactions as the models discussed in Section 3.2 make predictions about the link between overconfidence measures and stock market trading volume. The motivation for the use of the number of stock market purchases as a separate measure of trading volume is as follows. Buy and sell transactions are driven by different factors.[22] An investor who wants to buy a security has the choice between thousands of stocks whereas a sell decision only requires an analysis of the usually very few stocks in the investor's own portfolio (assuming that investors do not sell short).

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[19]See Glaser (2003) for descriptive statistics and further details. Not necessarily all orders are placed online but all investors traded via the internet at least once in our sample period. We consider all trades by these investors, i.e. we include the trades that were placed by telephone, for example.

[20]See Glaser (2003) for descriptive statistics.

[21]See, for example, Graham and Harvey (2003).

[22]See, for example, Odean (1999), p. 1294.

Furthermore, when investors buy a security they have to consider the future performance of the stocks they want to buy whereas they consider future as well as past performance when they choose a security to sell. The relevance of past performance for the selling decision is the finding of some empirical and experimental studies on the disposition effect, the tendency to sell winners too early and ride losers too long.[23] These studies suggest that there might be explanations for the sell decision, which are, for example, based on prospect theory (see Kahneman and Tversky (1979)).

Stock portfolio turnover in a given month is calculated as follows. We only consider stocks that are covered in Datastream. We calculate the sum of the absolute values of purchases and sales per month for each investor and divide this sum by the respective end-of-month stock portfolio position. To calculate the monthly average turnover per investor we only consider investors who have at least five end-of-month stock portfolio positions.

To summarize, overconfidence affects the expectations of future stock price performance. The fact that, when selling a security the effect of overconfidence is mixed with reference point dependent decision behavior of investors, justifies in our view a separate analysis of buy transactions. We conjecture that the effect of overconfidence is stronger when only buying transactions are considered.

4.3 Descriptive Statistics of all Investors and the Subgroup of Respondents to the Questionnaire

This subsection is concerned with the question of a possible sample selection bias. Table 1 compares descriptive statistics of the age, the number of transactions in all security categories (sum over the period from January 1997 to April 2001), the number of stock transactions (sum over the period from January 1997 to April 2001), the number of warrant transactions (sum over the period from January 1997 to April 2001), the average of the monthly stock portfolio value (in EUR), the average of the monthly stock portfolio turnover from January 1997 to April 2001, and the monthly stock portfolio performance (see Subsection 5.3 for details) for the 2,864 investors who did not answer and the 215

[23]See Shefrin and Statman (1985), Odean (1998a), and Weber and Camerer (1998) for empirical and experimental evidence on the disposition effect.

investors who answered (at least one question of) the questionnaire. The table contains means and medians of these variables as well as the number of observations of the respective variable (Obs.), and the number of observations of the respective variable in percent of the number of accounts in both groups (Obs. in % of no. of accounts). The last column presents the *p*-values of a two-sample Wilcoxon rank-sum test (Mann-Whitney test). Null hypothesis is that the two samples are from populations with the same distribution.

Table 1 shows that means and medians of all variables are similar in both groups. For example, the median age of investors in the two groups are 39 and 38, respectively. Furthermore, in both groups, about 95 % of investors are male (not shown in Table 1). Non-parametric tests show that none of the differences in both groups is significant (see last column of Table 1).[24] Furthermore, even the number of observations of the respective variable in percentages of the number of accounts in both groups are similar in both groups. For example, about 55 % of investors in both groups trade warrants. Thus, there is no indication of a sample selection bias.[25]

4.4 Measures of Overconfidence

We consider the following forms of overconfidence: miscalibration in knowledge questions, overconfidence in volatility estimates, and the better than average effect.[26] In this subsection, we will present the questions designed to measure overconfidence as well as the overconfidence measures obtained from the answers to these questions.

4.4.1 Miscalibration (misc)

The investors were asked to state upper and lower bounds of 90 % confidence intervals to five questions concerning general knowledge:

[24] See Glaser (2003) for further descriptive statistics.

[25] There are also no significant differences between investors who did not answer the questionnaire and those investors who answered *all* questions. Furthermore, there are no significant differences between investors who answered at least one question and investors who answered all questions.

[26] We also elicited illusion of control scores. These scores are neither correlated with the overconfidence scores presented in this paper nor with our trading volume measures. See the CEPR version of this paper for details (Glaser and Weber (2003)).

1) number of shares traded of Adidas-Salomon AG on Thursday, 5/10/2000, in Germany.
2) number of cars sold by BMW AG in March 2001 (worldwide).
3) number of Shell-petrol stations in Germany (end of the year 2000).
4) number of private customers of Deutsche Bank AG in Europe (May 2001).
5) number of drugstores in Germany (May 2001)).

This way of measuring the degree of miscalibration is widely used.[27] 137 of 215 Investors answered at least one question. 114 investors answered all questions.[28]

If the correct answer lies outside the 90 % confidence interval given by the investor we call this a surprise. For the questions which were actually answered by the respondents we calculate the percentage of surprises. Note, again, that the percentage of surprises of well calibrated investors should be 10 %. The mean percentage of surprises 75 %. The median is even higher (80 %). These figures are much higher than 10 %, the expected proportion of answers outside a well calibrated 90 % confidence interval. These findings are in line with prior research. Russo and Schoemaker (1992), for example, find percentage of surprises in the range from 42 % to 64 %. Other studies find percentages of surprises that are even closer to ours.[29]

4.4.2 Stock Market Forecasts (volest)

The investors were asked to provide upper and lower bounds of 90 % confidence intervals to five questions concerning stock market forecasts (Deutscher Aktienindex DAX, Nemax50 Performance Index, three German Stocks) for the end of the year 2001.[30] The use of confidence interval questions is widely used to elicit subjects' probability distributions,

[27]See Subsection 3.1.1 and, for example, Cesarini, Sandewall, and Johannesson (2005), Klayman, Soll, Gonzáles-Vallejo, and Barlas (1999), Biais, Hilton, Mazurier, and Pouget (2005), Soll and Klayman (2004).

[28]7 investors answered 1 question, 3 investors answered 2 questions, 4 investors answered 3 questions, and 9 investors answered 4 questions.

[29]See, for example, Hilton (2001), p. 42, and the references therein.

[30]The respondents to the first questionnaire had a forecast horizon of 21 weeks, respondents to the second questionnaire had a 14 week horizon. We also asked for the median estimate. See Glaser and Weber (2005) for details.

perceptions of expected returns, and variance estimations of stock returns.[31]

190 of 215 Investors answered at least one question. 165 investors answered all questions.[32]

We calculate the volatility forecasts of investors implied by their subjective confidence intervals as follows (see also Glaser and Weber (2005) or Graham and Harvey (2003)). We first transform these price or index value forecasts of individual k into returns[33]:

$$r(p)_i^k = \frac{x(p)_i^k}{value_i^{t_j}} - 1, \;\; p \in \{0.05, 0.5, 0.95\}, \;\; i \in \{1,2,3,4,5\}, \;\; j \in \{1,2\}, \;\; k \in \{1,\ldots,215\}. \tag{3}$$

t_1 indicates August 2nd, t_2 September 20th.[34] $x(p)$ denotes the p fractile of the stock price or index value forecast, $r(p)$ denotes the p fractile of the respective return forecast with $p \in \{0.05, 0.5, 0.95\}$. The five time series are denoted by i, $i \in \{1,2,3,4,5\}$.

The return volatility estimate of individual k, $k \in \{1,\ldots,215\}$, for time series i, $i \in \{1,2,3,4,5\}$, is calculated as follows (see Keefer and Bodily (1983)):[35]

$$stddev_i^k = \sqrt{0.185 \cdot (r(0.05)_i^k)^2 + 0.63 \cdot (r(0.50)_i^k)^2 + 0.185 \cdot (r(0.95)_i^k)^2 - (mean_i^k)^2}, \tag{4}$$

with $mean_i^k$ as given by

$$mean_i^k = 0.185 \cdot r(0.05)_i^k + 0.63 \cdot r(0.50)_i^k + 0.185 \cdot r(0.95)_i^k. \tag{5}$$

[31] See Subsection 3.1.2, for example, Deaves, Lüders, and Schröder (2004), Graham and Harvey (2003) and Siebenmorgen and Weber (2004) for a discussion.

[32] 4 investors answered 1 question, 6 investors answered 2 questions, 5 investors answered 3 questions, and 10 investors answered 4 questions.

[33] Some studies ask directly for returns, others ask for prices. Our method of elicitation was, among others, used by Kilka and Weber (2000).

[34] The exact time of response is not available. Furthermore, we do not know whether investors answered Thursday night, or on Friday, Saturday, or Sunday. Thus, we use the Thursday closing price in both groups to calculate expected returns. When we use the average of the Thursday closing price and the Friday closing price, the results are similar.

[35] For further details, see Glaser and Weber (2005).

Keefer and Bodily (1983) show numerically that equation (4) serves as a good three-point approximation of the standard deviation of a continuous random variable.

Glaser and Weber (2005) show that investors in the first group underestimate the volatility of stock returns (as measured by the standard deviation of historical returns). However, after the terror attacks of September 11, volatility forecasts are higher than before September 11. In two out of five cases, historical volatilities are overestimated.

The terror attacks of September 11 make it impossible to include the degree of the underestimation of the variance of stock returns directly in our analysis.[36] Therefore, we calculate the standardized deviation from the mean volatility estimate per investor in each of the two groups to rank investors according to their volatility estimates. For each investor group and for each time series we calculate the mean and the standard deviation of the volatility forecasts. For each investor we then calculate the standardized deviation from the mean volatility estimate by subtracting the mean volatility estimate from an investor's volatility estimate and by dividing this difference by the standard deviation of the volatility forecast. For each investor, we then calculate the average across these measures. The overconfidence measure volest based on the width confidence intervals for future stock price or index value is 1 minus this standardized standard deviation.

4.4.3 Better than Average Effect (bta1 and bta2)

We measure the degree of the better than average effect using the following two questions concerning skills and performance relative to others. Investors were asked to answer the following two questions:

1) What percentage of customers of your discount brokerage house have better skills (e.g. in the way they interpret information; general knowledge) than you at identifying stocks with above average performance in the future? (Please give a number between 0 % and 100 %)
2) What percentage of customers of your discount brokerage house had higher returns than you in the four-year period from January 1997 to December 2000? (Please give

[36]However, we present our analysis also for the subgroup of investors that answered the questionnaire before September 11.

a number between 0 % and 100 %)

We find that about half of the investors assess their skills and their abilities as above average. The median investor assesses her or his investment skills and her or his past performance as average.

For both questions, we calculate better than average scores of investor i (bta1$_i$ and bta2$_i$) as $\frac{50-\text{answer}_i}{50}$. These ratios yield 0 if respondents think they are average, 1 if they think they are better than everybody else, and -1 if they think to be worse than everybody else. The mean better than average scores are positive (0.12 and 0.06 for bta1 and bta2, respectively). This result indicates a slight better than average effect. High standard deviations are signs of large individual differences.

4.4.4 Correlation of Overconfidence Measures

Table 2 presents correlation coefficients of the four overconfidence measures described in the previous subsections as well as the significance level of each correlation coefficient and the number of observations used in calculating the correlation coefficient.

The two miscalibration scores based on subjective confidence intervals, misc and volest, are significantly positively correlated ($p = 0.0001$). The Spearman rank correlation coefficient is 0.3377. Although knowledge questions and stock market prediction questions are completely different tasks, we find stable individual differences in the degree of miscalibration. This finding is in line with several psychological studies (see, for example, Alba and Hutchinson (2000), Klayman, Soll, Gonzáles-Vallejo, and Barlas (1999), Pallier, Wilkinson, Danthiir, Kleitman, Knezevic, Stankov, and Roberts (2002), Soll (1996), Soll and Klayman (2004), and Stanovich and West (1998)). Usually, individual differences are especially strong when subjects are asked to state subjective confidence intervals (see, for example, Klayman, Soll, Gonzáles-Vallejo, and Barlas (1999), p. 240). Furthermore, Biais, Hilton, Mazurier, and Pouget (2005) also use ten confidence interval questions to rank people and show the psychometric validity of their miscalibration measure using the Cronbach alpha. Glaser, Langer, and Weber (2005) show that even five confidence interval questions are enough to reliably rank subjects with regard to their degree of miscalibration.

The two better than average scores, bta1 and bta2, have a correlation coefficient of 0.6461 ($p < 0.0001$). Investors who rank themselves as above average with regard to investment skills also assess their past portfolio performance as above average when compared to other investors. This finding, again, points to psychometric internal validity of this concept.

Most of the other correlations between overconfidence scores are insignificant. Some are even negative. The lack of correlation between our overconfidence measures is consistent with findings of other recent studies that are similar to this part of our study. Deaves, Lüders, and Luo (2003) measure miscalibration and the better than average effect using our questions or a slightly changed version of our questions.[37] Their correlation matrix also shows no significant positive correlations. Oberlechner and Osler (2003) find a negative (but statistically and economically insignificant) correlation between miscalibration and the better than average effect using a questionnaire similar to ours. Régner, Hilton, Cabantous and Vautier (2004) find little or now correlation between miscalibration, positive illusions such as unrealistic optimism, a general tendency to consider oneself as better than average, and illusion of control. Glaser, Langer, and Weber (2005) also find that miscalibration and the better than average effect are unrelated.[38]

Our results and the results in the literature can be summarized as follows:

- There are stable individual differences in reasoning or decision making competence (see Parker and Fischhoff (2005), Stanovich and West (1998), and Stanovich and West (2000)).
- There are stable individual differences in the degree of overconfidence within tasks (see Glaser, Langer, and Weber (2005), Jonsson and Allwood (2003), Klayman, Soll, Gonzáles-Vallejo, and Barlas (1999), Régner, Hilton, Cabantous and Vautier (2004)). This is consistent with the common modeling assumption in finance that investors with different degrees of overconfidence can be regarded as different investor "types" (see, for example, Benos (1998)).
- People often show different levels of overconfidence depending on the task or domain but the same rank-order over tasks or domains (see Jonsson and Allwood (2003),

[37]We also analyzed illusion of control. See Glaser and Weber (2003).

[38]Larrick, Burson, and Soll (2005) find, however, that miscalibration and the better than average effect can be positively correlated when they are both elicited for the same task or in the same domain.

p. 561, and Glaser, Langer, and Weber (2005)). Note, that to test the hypothesis that, the higher overconfidence the higher trading volume, not the *amount* or *level* of overconfidence but the *ranking* of investors is important.

- There is evidence that overconfidence and the rank order across people is stable over time (see Jonsson and Allwood (2003) or Glaser, Langer, and Weber (2005)).
- Overconfidence scores based on confidence interval tasks and better than average scores are not correlated (see Deaves, Lüders, and Luo (2003), Glaser, Langer, and Weber (2005), Oberlechner and Osler (2003), or Régner, Hilton, Cabantous and Vautier (2004)).

5 Overconfidence and Trading Volume: Empirical Results

5.1 Cross-Sectional Regressions

This section presents cross-sectional regression results on the relation between the three measures of trading volume (logarithm of the number of stock market transactions, logarithm of the number of stock market purchases, logarithm of mean monthly turnover) and the overconfidence measures described in Section 4.4 (see Tables 4, 5, and 6).[39]

Table 4 presents regression results on the relation between the logarithm of the number of stock market transactions and several explanatory variables that are known to affect financial decision making (a gender dummy variable, age, a warrant trader dummy variable, a high risk investment strategy dummy, the logarithm of mean monthly stock portfolio value, and information in hours per week).[40] Table 3 once again summarizes and defines dependent and independent variables of the cross-sectional regression analysis and presents their respective data source. The information variable is included to control for the level of commitment or involvement. The intuition behind this is the finding of some

[39]We use the natural logarithm of the stock portfolio value, and the three trading volume measures as these variables are positively skewed. Tests show, that we thus avoid problems like non-normality, non-linearity, and heteroscedasticity in the cross-sectional regression analysis. See Spanos (1986), chapter 21, especially, pp. 455-456, Davidson and McKinnon (1993), chapter 14, and Atkinson (1985), pp. 80-81.

[40]See, e.g., Barber and Odean (2001), Dorn and Huberman (2002), Glaser (2003), Glaser and Weber (2004), or Grinblatt and Keloharju (2001).

studies that overconfidence increases with the level of active involvement in a task.[41] We regard the information variable as a proxy for the level of involvement in the task of investing or trading.

In regressions (1) to (6), we consider all investors. In regressions (7) to (12), investors in the highest turnover quintile are excluded. This is motivated by the following finding. Glaser (2003) shows that the stock portfolio value in the highest turnover quintile is very low. The median value is about 10,000 Euro. The fact that the median of the average stock portfolio value across months is very low in the highest turnover quintile (median of monthly turnover is 166 %) is important. Thus, we cannot dismiss the argument that these accounts are entertainment accounts that are characterized by low portfolio values and high turnover ratios so that the potential effect of overconfidence is swamped.[42]

Regressions (1) and (7) report the results for the respective subgroup of investors that has responded to the questionnaire without an overconfidence measure. In each of the following regressions we include one overconfidence variable (Overconfidence).[43]

Only the better than average scores (Regressions (5), (11), and (12)) are significantly positively related with the number of stock market transactions. However, miscalibrated investors do not exhibit a higher trading volume.

Other variables that significantly affect the number of stock market transactions are the warrant trader dummy variable (positive sign) and the mean monthly stock portfolio value (positive sign). Investors who trade warrants do trade more stocks and the higher the value of the stock portfolio the higher the number of transactions.[44] The warrant trader dummy variable might be interpreted as a measure of investor sophistication. Bank-issued warrants are comparable to options but with some institutional differences. For example,

[41] See, for example, Presson and Benassi (1996), p. 496.

[42] Glaser (2003) presents further characteristics of investors in the highest turnover quintile which strengthen this conjecture. For example, about 70 % of investors in the highest turnover quintile actively trade warrants and only 1.39 % of these investors use their account for retirement savings.

[43] Note, that we assume that overconfidence is a stable individual trait and thus constant over time. This assumption is consistent with static overconfidence models presented Subsection 3.2. Experimental studies indeed show stability over time for the concept of miscalibration (see, for example, Jonsson and Allwood (2003) or Glaser, Langer, and Weber (2005)). We analyze the implications of dynamic overconfidence models with a time-varying degree of overconfidence in Subsection 5.3.

[44] See Glaser (2003) for further results on the general determinants of trading volume in the whole data set.

warrants are always issued by financial institutions (see Schmitz, Glaser, and Weber (2005) for details).

Perhaps surprising, gender is not significantly related to our trading volume measures. This contradicts the findings of Barber and Odean (2001) who find that men trade more than women. However, our results are consistent with other studies analyzing the behavior of investors such as Dorn and Huberman (2002), Glaser (2003), Glaser and Weber (2004), and Grinblatt and Keloharju (2001). These studies show that the sign and the significance of the gender variable depends on the specification of the regression.

Buy and sell transactions are driven by different factors. As hypothesized in Section 4.2, the effect of overconfidence is stronger when only buy transactions are considered. Therefore, we analyze the number of purchases separately. The results show that our conjecture is confirmed. Table 5 presents regression results on the relation between the logarithm of the number of stock market purchases and several explanatory variables. Both bta1 and bta2 are significant in Regressions (5), (11), and (12). The t-values are, as hypothesized, higher than in the respective regressions in Table 4.

Table 6 presents regression results on the relation between the logarithm of mean monthly turnover and the same explanatory variables. None of the overconfidence measures is significantly related to turnover in Regressions (1) to (6). The main determinants of turnover are the warrant trader dummy (positive sign) and the mean monthly stock portfolio value (negative sign). The last observation is consistent with the finding that the median of the average stock portfolio value across months is very low in the highest turnover quintile.

When we exclude investors in the highest turnover quintile and run the regressions just for the remaining investors, Tables 4, 5, and 6 show that the effect of the better than average scores on trading volume are always stronger, as predicted. The miscalibration score (misc) has no significant impact and the signs of the coefficients are, contrary to theory, mainly negative (Regression (9) in Table 6 is the only exception). Furthermore, the adjusted R-squared values in in Regressions (7) to (12) are usually higher than in the respective Regressions (1) to (6) when all respondents to the questionnaire are analyzed. This stresses our previous conjecture that the level of trading volume in the highest turnover quintile are driven by factors that are unobserved. In addition, the adjusted R-squared values in Regressions (5), (6), (11), and (12) are higher when the better than average scores are included when compared to the respective Regressions (1) and (7) in each table without an overconfidence measure as explanatory variable. Thus, the better than average scores explain additional variation of the trading volume measures. This increase in the adjusted R-squared values is higher in Regressions (8) to (12) than in the respective Regressions (2) to (6) that analyze all respondents to the questionnaire suggesting, again, that the accounts with the highest turnover values might be entertainment accounts.

Note, however, that the increase of the adjusted R-squared values as a result of the inclusion of the better than average scores in the regressions compared to the Regressions (1) and (7) is not very big. These results might be interpreted in the way that behavioral or psychological factors matter but they are by far not the whole story. Other (rational or unobserved (rational or psychological)) factors also determine trading volume.

5.2 Robustness Checks

All the results in this subsection are robust as unreported regression results show. The better than average scores remain significant for different sets of explanatory variables. Miscalibration scores are never significantly positive. Furthermore, most of the overconfidence measures are not significantly correlated with other explanatory variables. Only the better than average scores are significantly positively related to the information variable. In addition, the overconfidence measures are not significantly different for men/women, warrant-trader/non-warrant-trader, and investors that describe their investment strategy as high-risk/not high-risk. Thus, our overconfidence measures seem to capture investor characteristics that differ from other determinants of trading volume.

The results also hold for different turnover definitions. We also analyzed another measure of trading activity, the average volume per transaction. The models presented in Subsection 3.2 also predict larger bets for overconfident investors. We find that the average volume per transaction is almost completely driven by the stock portfolio value: the higher the stock portfolio value, the higher the average volume per transaction (see also Glaser (2003)). When we scale the average volume per transaction by the stock portfolio value, the only significant variable is, again, the stock portfolio value, but with a negative sign.

We also interpreted the number of stock transactions and the number of stock purchases as (overdispersed) count data (see, for example, Wooldridge (2002) and Winkelmann (2003)). Overdispersion means that the variance of the number of stock transactions is larger than the mean of the number of stock transactions. In our data set, the variance of the number of stock transactions is 32,533 whereas the mean of the number of stock transactions is 105 (see Glaser (2003)). When we use appropriate regression models (Poisson regression model, negative binomial regression model), the results and conclusions are similar to the results of the ordinary least squares regressions presented in this subsection.

We used a logarithmic transformation of some regression variables (see footnote 39). An applied-econometricians' rule-of-thumb to avoid problems like non-normality, non-linearity, and heteroscedasticity is to use the logarithmic transformation of positively skewed variables (see Spanos (1986)). The transformed variables are approximately normally distributed. A more formal way to transform variables is to use the Box-Cox transformation. In regressions using the Box-Cox transformation of dependent and independent variables, our basic results are even stronger.

5.3 Portfolio Performance and Overconfidence

Up to this point in the paper we maintained the assumption that overconfidence is a stable individual trait and thus constant over time. This assumption is consistent with overconfidence models presented in Subsection 3.2 and experimental evidence (see Jonsson and Allwood (2003) and Glaser, Langer, and Weber (2005)). Note, that this assumption is necessary to argue that a high overconfidence score, measured at the end of the sample period, leads to high trading volume during the sample period, as overconfidence is constant through time and it does not matter when overconfidence is measured. However, there are other models assuming that overconfidence dynamically changes over time (see, e.g., Gervais and Odean (2001)). This modeling assumption is usually motivated by psychological studies that find biased self-attribution (see Wolosin, Sherman, and Till (1973), Langer and Roth (1975), Miller and Ross (1975), Schneider, Hastorf, and Ellsworth (1979)): People overestimate the degree to which they are responsible for their own success. In these overconfidence models, the degree of overconfidence is a function of past investment success, i.e. the higher the performance in the past the higher the degree of overconfidence at the end of the period (learning-to-be-overconfident hypothesis; Gervais and Odean (2001)).[45] There is another story that involves a time-varying degree of overconfidence. Assume that (some) investors are overconfident at the start of the sample period. As a consequence, they trade more. If high trading volume is associated with low returns, the most overconfident investors at the beginning of the sample period might end up with the lowest overconfidence measures at the end of the period as a consequence of high trading volume (and low returns) during the sample period.

To empirically test these two stories, we correlate overconfidence scores with the performance of the investors in the past.[46] Moreover, we are able to analyze whether investors who assess their investment skills or performance as above average compared to others really had above average performance in the past. Furthermore, we analyze the relation between portfolio performance and portfolio turnover.

We calculate the monthly gross portfolio performance of each investor making the following simplifying assumptions:

- We assume that all stocks are bought and sold at the end of the month.
- We ignore intra-month trading.

Barber and Odean (2000) show that these simplifying assumptions do not bias the measurement of portfolio performance.

The gross portfolio return R_{ht}^{gr} of investor h in month t is calculated as follows:

$$R_{ht}^{gr} = \sum_{i=1}^{S_{ht}} w_{iht} R_{it} \qquad \text{with} \qquad w_{iht} = \frac{P_{it} n_{iht}}{\sum_{i=1}^{S_{ht}} P_{it} n_{iht}} \tag{6}$$

R_{it} is the return of stock i in month t, S_{ht} is the number of stocks held by individual h in month t, P_{it} is the price of stock i at the beginning of month t, and n_{iht} is the number

[45]See Glaser, Nöth, and Weber (2004) for a further discussion of these models.

[46]Another possibility to test the learning-to-be-overconfident hypothesis is to analyze the link between past returns and trading volume. See Section 6 for further details and Glaser and Weber (2004) for an empirical study of this issue.

of stocks of company i held by investor h in month t. w_{iht} is the beginning-of-month-t market value of the holding of stock i of investor h divided by the beginning-of-month-t market value of the whole stock portfolio of investor h.

The cross-sectional distribution of the monthly gross returns is similar to the results in Barber and Odean (2000), Table IV, p. 791. We observe a large cross-sectional variation in the performance across investors. When we exclude investors with stock positions in 12 or fewer months, we find gross returns between -16% and $+24\%$ *per month*. On average, investors underperform relevant benchmarks. For example, the arithmetic average monthly return of the German blue chip index DAX from January 1997 to March 2001 is 2.02% whereas the mean gross monthly return of investors in our data set is 0.54%.

We find that investors who trade more do not have higher monthly gross returns. We cannot reject the hypothesis that monthly gross returns are equal in turnover quintiles using a non-parametric Kruskal-Wallis test.[47]

Furthermore, we do not find significant correlations between the monthly gross return in our 51 month period and our overconfidence measures.[48] High returns in the past do not lead to high overconfidence measures in our questionnaire at the end of the sample period. Thus, we do not find support for the learning-to-be-overconfident hypothesis, i.e. a high degree of overconfidence as a result of past investment success. Furthermore we do not find support for the second story presented at the beginning of this subsection as we do not find a significant correlation between overconfidence and (gross) performance.

The results of this subsection might be explained by the following findings. Investors are not able to give a correct assessment of their own past realized portfolio performance. We asked the investors to give an estimate of the past realized stock portfolio performance

[47] Note, that Barber and Odean (2000) find exactly the same result for gross returns (Barber and Odean (2000), Figure 1, p. 775). The underperformance of investors who trade more is *completely* driven by transaction costs.

[48] We also checked the robustness of this result. Past returns over the past 12, 6, and 3 months are also not related to our overconfidence measures. Note, however, that there are about four months between the end of our observation period and the date the questionnaire was answered. Furthermore, cross-sectional regressions with an overconfidence measure as dependent variable and several sets of explanatory variables (past realized returns over various horizons; variables mentioned in Table 1) do not yield a clear picture or significant results. This complements the findings mentioned before that our overconfidence measures are not significantly correlated with other explanatory variables. We conclude that our overconfidence scores measure traits or investor characteristics that are orthogonal to past returns or other explanatory variables.

of their account at the online broker. Glaser and Weber (2004) show that the correlation between the assessment of past (absolute) portfolio performance and realized portfolio performance is negative (but insignificant). Furthermore, they find that past market returns have a stronger impact on trading activity than past portfolio returns of an investor. This finding is consistent with a result of Statman, Thorley, and Vorkink (2004) who state that "not only does that impact of past market returns on a typical security's trading activity survive the inclusion of lagged security returns in the same regression, it appears that the lagged market return impact is actually larger" (Statman, Thorley, and Vorkink (2004), p. 22). These findings are no surprise when investors have a better knowledge of market returns compared to the returns of the stocks in their own portfolio.

Moreover, investors are not able to give a correct assessment of their performance relative to others. We grouped all investors in percentiles based on their past realized stock portfolio performance. The correlation between the assessment of past portfolio performance compared to others (via percentiles; see the bta2 measure in Subsection 4.4.3) and actual percentile is negative (but insignificant). Furthermore, the difference between the actual return percentile of the respective investor and the self-assessed percentile is positive on average (this difference is positive if an investor thinks, for example, that only 25% of the other investors had higher portfolio returns in the past even though 30 % of the investors in the sample actually had higher returns). Thus, investors overestimate their relative position in terms of return percentiles. The result that there is a poor correlation between such subjective and objective measures or between self-ratings of skill and actual performance is a common finding in the literature (see, for example, Larrick, Burson, and Soll (2005) or Dunning, Heath, and Suls (2004) for references.)

The results of this subsection can be summarized as follows:

- Investors who trade more have, on average, the same gross monthly returns as investors who trade less.
- Investment success in the past does not lead to high overconfidence scores at the end of the sample period.
- Investors have difficulties in estimating their own past realized stock portfolio performance.

- Investors who think that they had above average performance actually did not have above average performance in the past.

6 Discussion

We show that overconfidence as measured by calibration questions is not sigificantly related to trading volume. This result is inconsistent with theory but consistent with findings of Biais, Hilton, Mazurier, and Pouget (2005). Note, again, that overconfidence models almost exclusively model overconfidence via miscalibrated investors. Why is miscalibration not positively related to trading volume, as predicted by overconfidence models? One important point to remember is that the link between miscalibration and trading volume has never been shown or even analyzed empirically or experimentally. Biais, Hilton, Mazurier, and Pouget (2005) and our study are the only exceptions that analyze this link.

We find that investors who think that they are above average do trade more. Deaves, Lüders, and Luo (2003) measure miscalibration and the better than average effect using questions similar to ours and correlate these overconfidence scores with trading activity in an experimental asset market. They also find that people who think that they are above average trade more.[49] Oberlechner and Osler (2003), p. 27, also argue and find that the better than average effect, not miscalibration, explains excess trading volume using survey data from U.S. currency market professionals. Our results are also consistent with Graham, Harvey, and Huang (2005). They find that investors who feel competent trade more often. Our better than average questions can also be interpreted as perceived competence. Our findings are also related to Hales (2005). He shows experimentally that a willingness to engage in speculative trade in laboratory markets is largely driven by a failure of traders to account for information about value implicit in other trader's actions. He argues that this behavior arises because traders construct myopic mental models that

[49] Furthermore, Deaves, Lüders, and Luo (2003) find that the degree of miscalibration is related to trading activity which is consistent with overconfidence models. However, experimental subjects were told that those who had exhibited higher general knowledge in the questionnaire would receive more accurate private noisy signals in the experimental asset market. Deaves, Lüders, and Luo (2003) even admit that "overconfident people will tend to think that their answers are more accurate, implying that their signals are more revealing and trade accordingly" (Deaves, Lüders, and Luo (2003), p. 8). Thus, their "miscalibration score" just captures another facet of the better than average effect.

ignore the perspective of other traders. This can be explained by the fact that some investors think that they are better than others.

The finding that investors who think that they are above average do trade more is in line with the differences of opinion literature. Although this strand of literature is, as discussed in Subsection 3.2, usually not regarded as a part of the behavioral finance literature and although differences of opinion can be motivated rationally we propose a psychological motivation of the differences in opinions assumption. This conjecture is not completely new (see Shiller (1999), Barberis and Thaler (2003), Hong and Stein (2003), and Diether, Malloy, and Scherbina (2002)). In their model of trading in speculative markets based on differences of opinion among traders, Harris and Raviv (1993) state that, "we assume that each speculator is absolutely convinced that his or her model is correct. Indeed, each group believes the other group is basing its decision on an incorrect model (i.e. is irrational in this sense)".[50] Although Harris and Raviv (1993) stress that they "maintain the assumption of rational agents", this assumption is in line with the finding that people think that they are above average in terms of investment skills. Shiller (1999), for example, argues that "if we connect the phenomenon of overconfidence with the phenomenon of anchoring, we see the origins of differences of opinion among investors, and some of the source of the high volume of trade among investors. ... Apparently, many investors do feel that they do have speculative reasons to trade often, and apparently this must have to do with some tendency for each individual to have beliefs that he or she perceives as better than others' beliefs. It is as if most people think they are above average."[51].

There are other studies which show empirically that differences in opinion creates trading volume. Bamber, Barron, and Stober (1999) and Antweiler and Frank (2004) are two examples. Bamber, Barron, and Stober (1999) measure differential interpretations using data on analysts' revisions of forecasts of annual earnings after the announcement of quarterly earnings. They find that differential interpretations explain a significant amount of trading. Antweiler and Frank (2004) study the effect of more than 1.5 million messages posted on Yahoo! Finance and Raging Bull about the 45 companies in the Dow Jones Industrial Average and the Dow Jones Internet Index. They find that disagreement among

[50] Harris and Raviv (1993), p. 480.

[51] Shiller (1999), pp. 1322-1323.

the posted Internet messages is associated with increased trading volume. Glaser and Weber (2004) find that both past market returns as well as past portfolio returns affect trading activity of individual investors. However, the effect of market returns on subsequent trading volume is stronger. These findings show that an overconfidence story (or, to be more precise, the learning-to-be-overconfident hypothesis) is at best only one part of the story because as it is unclear why past market returns should affect trading volume. This is even more so as Glaser and Weber (2004), using survey data of this investor sample, show that individual investors in this investor sample are unable to give a correct estimate of their own past realized stock portfolio performance. One explanation of why past market returns should affect trading activity is that high past market returns might increase differences of opinion. In their survey of CFO stock return expectations, Graham and Harvey (2003) show that past market returns are related to differences of opinion. High past (absolute) returns lead to higher differences of opinion.[52]

Besides mentioning the strengths of our approach - the ability to directly test the hypothesis that a higher degree of overconfidence leads to higher trading volume - we want to discuss some possible weaknesses as well. We conducted the questionnaire part of our study via the internet. Internet experiments increase the variance of responses when compared to experiments in a controlled laboratory environment (Anderhub, Müller, and Schmidt (2001)). Thus, too much noise might be a possible reason why we are unable to prove a link between miscalibration scores and measures of trading volume. We note, however, that Biais, Hilton, Mazurier, and Pouget (2005) find results similar to ours in a controlled environment. Furthermore, if we find a significant effect despite the noise inherent in internet questionnaires, such as in the case of the better than average scores, we can be very confident about the presence of this link in reality.

[52] Although Graham and Harvey (2003) find that both large negative and positive returns affect differences of opinion, we argue that negative returns that are associated with differences of opinion do not lead to the same level of trading activity as positive returns in connection with differences of opinion. Negative returns are associated with paper losses and investors usually are reluctant to realize these paper losses. See Shefrin and Statman (1985), Odean (1998a), and Weber and Camerer (1998).

7 Conclusion

The contribution of this paper is to measure overconfidence of a group of online broker investors in various dimensions (miscalibration, volatility estimates, better than average effect) and to analyze whether these overconfidence measures are significantly related with trading volume of individual investors.

One implication of our study is that one has to be careful when deriving theoretical assumptions from psychological experiments unrelated to financial tasks. It is important to specify what kind of overconfidence may be influencing trading behavior. Hirshleifer (2001), for example, argues that "it is often not obvious how to translate preexisting evidence from psychological experiments into assumptions about investors in real financial settings. Routine experimental testing of the assumptions and conclusions of asset-pricing theories is needed to guide modeling."[53] It is especially important for descriptive behavioral finance theories to model as precisely as possible.

We find that investors who think that they are above average trade more and are thus able to confirm other recent papers (Deaves, Lüders, and Luo (2003), Graham, Harvey, and Huang (2005), Hales (2005)). One of the most striking results of our study is that overconfidence, as measured by calibration questions, is unrelated to trading volume. This result seems to be robust as Biais, Hilton, Mazurier, and Pouget (2005) report similar findings. These results are even more important as theoretical models that incorporate overconfident investors mainly motivate this assumption by the calibration literature and model overconfidence as underestimation of the variance of signals (or overestimation of their precision), i.e. by too tight confidence intervals. In connection with other recent findings, we conclude that the usual way of motivating and modeling overconfidence which is mainly based on the calibration literature has to be treated with caution.

But why is it important to look at subtle modeling differences? Descriptive models have to be as precise as possible and have to rely on empirical and experimental observations. This is also discussed in Hales (2005). He provides evidence that a willingness to engage in speculative trade is largely driven by a failure to account for information about value

[53] Hirshleifer (2001), p. 1577.

implicit in other trader's actions. Unlike overconfidence models, which focus on erroneous estimates of signal precision, these participants do not trade too much because they underestimate the error of noisy signals. Rather, participants engage in too much speculative trade because they tend not to think about the implications of disagreement. The evidence presented in Hales (2005) also supports the general technique of modeling investor behavior using differences of opinion by showing that, even though traders are capable of adjusting for other's behavior, they will not naturally do so. He also argues that, as a result, investors might often act like they believe they are better than average traders (or have better than average information).

There are several suggestions for future research. We measure various facets of overconfidence. Numerous studies suggest or argue, at least implicitly, that these manifestations of overconfidence are related. In other words: answers to experimental tasks should be positively correlated. Our study is a hint that this need not be the case. Future research should further analyze whether overconfidence is a robust phenomenon across several tasks that are often assumed to be related. Furthermore, our way of empirically evaluating behavioral finance models - the correlation of economic and psychological variables and the combination of psychometric measures of judgment biases (such as overconfidence scores) and field data - seems to be a promising way to better understand which psychological phenomena drive economic behavior. This empirical methodology should be routinely used to guide modeling.

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Table 1: **Descriptive Statistics: Investors who Answered versus Investors who did not Answer the Questionnaire**

This table compares descriptive statistics of the age, the number of transactions in all security categories (sum over the period from January 1997 to April 2001), the number of stock transactions (sum over the period from January 1997 to April 2001), the number of warrant transactions (sum over the period from January 1997 to April 2001), the average of the monthly stock portfolio value (in EUR), the average of the monthly stock portfolio turnover from January 1997 to April 2001, and the monthly stock portfolio performance (see Subsection 5.3 for details) for the 2,864 investors who did not answer and the 215 investors who answered the questionnaire. The table contains means and medians of these variables as well as the number of observations of the respective variable (Obs.), and the number of observations of the respective variable in percent of the number of accounts in both groups (Obs. in % of no. of accounts). The last column presents the p-values of a two-sample Wilcoxon rank-sum test (Mann-Whitney test). Null hypothesis is that the two samples are from populations with the same distribution.

		Investors who did not answer questionnaire	Investors who answered questionnaire	p-value (Mann-Whitney test)
No. of accounts		2,864	215	
Age	Mean	40.92	40.02	0.2942
	Median	39	38	
	Obs.	2,369	183	
	Obs. in % of no. of accounts	82.72	85.12	
Transactions	Mean	184.89	156.17	0.5621
	Median	103	105	
	Obs.	2,864	215	
	Obs. in % of no. of accounts	100.00	100.00	
Stock transactions	Mean	106.37	92.87	0.9422
	Median	54	52	
	Obs.	2,793	205	
	Obs. in % of no. of accounts	97.52	95.35	
Warrant transactions	Mean	88.99	69.81	0.8194
	Median	27	29	
	Obs.	1530	120	
	Obs. in % of no. of accounts	53.42	55.81	
Stock portfolio value	Mean	36590.83	37061.01	0.5614
	Median	15629.70	15887.10	
	Obs.	2,762	202	
	Obs. in % of no. of accounts	96.44	93.95	
Stock portfolio turnover	Mean	1.37	1.21	0.9692
	Median	0.33	0.33	
	Obs.	2,675	199	
	Obs. in % of no. of accounts	93.40	92.56	
Stock portfolio performance	Mean	0.0056	0.0030	0.4538
	Median	0.0057	0.0053	
	Obs.	2,598	195	
	Obs. in % of no. of accounts	90.71	90.70	

Table 2: **Correlation of Overconfidence Variables**

This table presents pairwise Spearman rank correlation coefficient between our overconfidence measures described in Subsection 4.4 as well as the significance level of each correlation coefficient (in parentheses) and the number of observations used in calculating the correlation coefficient. misc denotes the percentage of surprises in knowledge questions. volest is an overconfidence measure based on the width of confidence intervals for future stock prices or index values. bta1 is a better than average score based on self-assessment of investment skills in relation to other investors' investment skills. bta2 denotes a better than average score based on self-assessment of past performance in relation to other investors' past performance. * indicates significance at 10%; *** indicates significance at 1%.

	misc	volest	bta1	bta2
misc	1			
	137			
volest	0.3377	1		
	(0.0001)***			
	137	190		
bta1	-0.0327	-0.0304	1	
	(0.7040)	(0.6774)		
	137	190	212	
bta2	0.1708	-0.0077	0.6461	1
	(0.0460)*	(0.9164)	(< 0.0001)***	
	137	190	212	212

Table 3: **Definition of Variables**

This table summarizes and defines dependent and independent variables of the cross-sectional regression analysis and presents their respective data source.

Variables	Data Source	Description
Gender (dummy)	Self-reported data collected by the online broker at the time each investor opened the account.	Dummy variable which takes the value 1 when the investor is male.
Age	Self-reported data collected by the online broker at the time each investor opened the account.	Age of investor.
High risk (dummy)	Self-reported data collected by the online broker at the time each investor opened the account.	Dummy variable which takes the value 1 when the investment strategy is characterized as high-risk.
Warrant trader (dummy)	Transaction data	Dummy variable which takes the value 1 when the investor trades warrants at least once in the period form January 1997 to April 2001.
Number of stock transactions	Transaction data	Number of stock transactions (Sum over the period from January 1997 to April 2001).
Number of stock purchases	Transaction data	Number of stock purchases (Sum over the period from January 1997 to April 2001).
Turnover	Transaction data	Average of the monthly turnover from January 1997 to April 2001.
Portfolio value	Transaction data	Average of the monthly portfolio value of stocks that were bought in DEM or EUR and that are covered in Datastream.
Information	Questionnaire	Information in hours per week.
misc	Questionnaire	Percentage of surprises in knowledge questions.
volest	Questionnaire	Overconfidence measure based on the width of confidence intervals for future stock prices or index values.
bta1	Questionnaire	Better than average score based on self-assessment of investment skills in relation to other investors' investment skills.
bta2	Questionnaire	Better than average score based on self-assessment of past performance in relation to other investors' past performance.

Table 4: **The Number of Stock Market Transactions and Measures of Overconfidence: Cross-Sectional Regressions**

This table presents regression results on the relation between the logarithm of the number of stock market transactions and several explanatory variables (a gender dummy variable (the variable takes the value 1 if the investor is male), age, a warrant trader dummy variable (the variable takes the value 1 if the investor trades warrants at least once in the time period from January 1997 until April 2001), a high risk dummy (the variable takes the value 1 if the investor classifies her investment strategy as high risk), the logarithm of mean monthly stock portfolio value, information in hours per week). In regressions (1) to (6), we consider all investors. In regressions (7) to (12), investors in the highest turnover quintile are excluded. Regressions (1) and (7) report the results for the respective subgroup of investors that has responded to the questionnaire without an overconfidence measure. In each of the following regressions we include one overconfidence variable (Overconfidence). Absolute value of t statistics are in parentheses. * indicates significance at 10%; ** indicates significance at 5%; *** indicates significance at 1%.

Dependent variable	(1) ln(Number of stock market transactions)	(2) ln(Number of stock market transactions)	(3) ln(Number of stock market transactions)	(4) ln(Number of stock market transactions)	(5) ln(Number of stock market transactions)	(6) ln(Number of stock market transactions)	(7) ln(Number of stock market transactions)	(8) ln(Number of stock market transactions)	(9) ln(Number of stock market transactions)	(10) ln(Number of stock market transactions)	(11) ln(Number of stock market transactions)	(12) ln(Number of stock market transactions)
	All respondents to the questionnaire						Highest turnover quintile excluded					
Overconfidence variable	-	misc	volest	volest (first group, before Sept 11)	bta1	bta2	-	misc	volest	volest (first group, before Sept 11)	bta1	bta2
Gender	0.082	-0.425	-0.159	-0.038	0.233	0.212	0.206	-0.337	-0.176	-0.071	0.279	0.263
	(0.22)	(0.87)	(0.35)	(0.08)	(0.58)	(0.52)	(0.50)	(0.62)	(0.37)	(0.14)	(0.69)	(0.64)
Age	-0.007	-0.012	-0.006	0.015	-0.005	-0.005	-0.006	-0.009	-0.006	0.013	-0.003	-0.002
	(0.82)	(1.20)	(0.65)	(1.39)	(0.63)	(0.56)	(0.75)	(0.82)	(0.73)	(1.16)	(0.41)	(0.22)
Warrant trader	0.850	0.797	0.850	1.033	0.882	0.885	0.768	0.662	0.749	0.807	0.782	0.797
	(5.46)***	(4.13)***	(5.01)***	(5.10)***	(5.60)***	(5.57)***	(4.72)***	(3.23)***	(4.24)***	(3.93)***	(4.88)***	(4.93)***
High risk	-0.207	-0.166	-0.224	-0.362	-0.181	-0.215	-0.382	-0.178	-0.507	-0.797	-0.315	-0.349
	(0.84)	(0.55)	(0.81)	(1.16)	(0.74)	(0.87)	(1.37)	(0.52)	(1.55)	(2.17)**	(1.15)	(1.27)
ln(Portfolio value)	0.524	0.538	0.548	0.504	0.518	0.511	0.561	0.530	0.588	0.541	0.552	0.543
	(9.55)***	(7.89)***	(8.94)***	(6.77)***	(9.36)***	(9.07)***	(9.74)***	(7.36)***	(9.11)***	(7.07)***	(9.73)***	(9.44)***
Information	-0.004	-0.006	-0.006	-0.022	-0.012	-0.009	0.006	0.000	0.004	0.004	-0.005	-0.004
	(0.35)	(0.46)	(0.45)	(1.12)	(0.96)	(0.71)	(0.53)	(0.01)	(0.33)	(0.19)	(0.40)	(0.31)
Overconfidence		-0.359	-0.018	-0.149	0.447	0.295		-0.391	0.010	-0.126	0.571	0.523
		(0.97)	(0.17)	(1.08)	(2.11)**	(1.39)		(0.97)	(0.09)	(0.94)	(2.70)***	(2.35)**
Constant	-1.296	-0.441	-1.284	-1.619	-1.474	-1.389	-1.963	-0.682	-1.805	-2.059	-2.084	-2.017
	(2.02)**	(0.50)	(1.72)*	(1.79)*	(2.24)**	(2.09)**	(2.92)***	(0.70)	(2.33)**	(2.21)**	(3.15)***	(3.04)***
Observations	171	107	152	99	168	168	134	85	118	74	133	133
Adjusted R-squared	0.41	0.43	0.41	0.47	0.42	0.41	0.47	0.43	0.46	0.53	0.49	0.48

Table 5: **The Number of Stock Market Purchases and Measures of Overconfidence: Cross-Sectional Regressions**

This table presents regression results on the relation between the logarithm of the number of stock market purchases and several explanatory variables (a gender dummy variable (the variable takes the value 1 if the investor is male), age, a warrant trader dummy variable (the variable takes the value 1 if the investor trades warrants at least once in the time period from January 1997 until April 2001), a high risk dummy (the variable takes the value 1 if the investor classifies her investment strategy as high risk), the logarithm of mean monthly stock portfolio value, information in hours per week). In regressions (1) to (6), we consider all investors. In regressions (7) to (12), investors in the highest turnover quintile are excluded. Regressions (1) and (7) report the results for the respective subgroup of investors that has responded to the questionnaire without an overconfidence measure. In each of the following regressions we include one overconfidence variable (Overconfidence). Absolute value of t statistics are in parentheses. * indicates significance at 10%; ** indicates significance at 5%; *** indicates significance at 1%.

Dependent variable	(1) ln(Number of stock market purchases)	(2) ln(Number of stock market purchases)	(3) ln(Number of stock market purchases)	(4) ln(Number of stock market purchases)	(5) ln(Number of stock market purchases)	(6) ln(Number of stock market purchases)	(7) ln(Number of stock market purchases)	(8) ln(Number of stock market purchases)	(9) ln(Number of stock market purchases)	(10) ln(Number of stock market purchases)	(11) ln(Number of stock market purchases)	(12) ln(Number of stock market purchases)
	All respondents to the questionnaire						Highest turnover quintile excluded					
Overconfidence variable	-	misc	volest	volest (first group, before Sept 11)	bta1	bta2	-	misc	volest	volest (first group, before Sept 11)	bta1	bta2
Gender	0.067	-0.332	-0.129	0.050	0.207	0.189	0.177	-0.243	-0.149	-0.013	0.253	0.239
	(0.19)	(0.72)	(0.30)	(0.11)	(0.54)	(0.49)	(0.45)	(0.47)	(0.33)	(0.03)	(0.66)	(0.62)
Age	-0.010	-0.014	-0.008	0.015	-0.008	-0.008	-0.009	-0.011	-0.008	0.013	-0.006	-0.004
	(1.31)	(1.49)	(0.95)	(1.50)	(1.10)	(1.02)	(1.16)	(1.04)	(0.89)	(1.27)	(0.78)	(0.55)
Warrant trader	0.788	0.732	0.804	0.933	0.821	0.825	0.699	0.602	0.696	0.691	0.715	0.732
	(5.37)***	(4.01)***	(5.02)***	(4.95)***	(5.54)***	(5.52)***	(4.51)***	(3.09)***	(4.13)***	(3.58)***	(4.71)***	(4.78)***
High risk	-0.065	0.018	-0.032	-0.115	-0.031	-0.068	-0.183	0.108	-0.206	-0.371	-0.097	-0.129
	(0.27)	(0.06)	(0.12)	(0.38)	(0.13)	(0.28)	(0.67)	(0.31)	(0.63)	(1.00)	(0.36)	(0.48)
ln(Portfolio value)	0.524	0.539	0.549	0.479	0.516	0.508	0.546	0.510	0.577	0.507	0.535	0.524
	(10.06)***	(8.28)***	(9.43)***	(6.89)***	(9.85)***	(9.54)***	(9.88)***	(7.33)***	(9.30)***	(7.02)***	(9.86)***	(9.54)***
Information	0.002	-0.000	0.001	-0.019	-0.006	-0.003	0.010	0.004	0.008	0.002	-0.001	-0.001
	(0.17)	(0.00)	(0.08)	(1.05)	(0.50)	(0.27)	(0.89)	(0.34)	(0.70)	(0.09)	(0.11)	(0.05)
Overconfidence		-0.390	-0.008	-0.143	0.441	0.317		-0.413	0.027	-0.126	0.576	0.552
		(1.11)	(0.08)	(1.11)	(2.21)**	(1.59)		(1.07)	(0.25)	(0.99)	(2.86)***	(2.61)**
Constant	-1.693	-0.985	-1.820	-1.986	-1.856	-1.770	-2.176	-0.990	-2.221	-2.261	-2.286	-2.221
	(2.79)***	(1.18)	(2.58)**	(2.37)**	(2.99)***	(2.83)***	(3.39)***	(1.06)	(3.00)***	(2.58)**	(3.64)***	(3.52)***
Observations	170	106	151	98	167	167	133	84	117	73	132	132
Adjusted R-squared	0.43	0.45	0.44	0.48	0.44	0.43	0.47	0.44	0.47	0.51	0.50	0.49

Table 6: **Turnover and Measures of Overconfidence: Cross-Sectional Regressions**

This table presents regression results on the relation between the logarithm of mean monthly turnover and several explanatory variables (a gender dummy variable (the variable takes the value 1 if the investor is male), age, a warrant trader dummy variable (the variable takes the value 1 if the investor trades warrants at least once in the time period from January 1997 until April 2001), a high risk dummy (the variable takes the value 1 if the investor classifies her investment strategy as high risk), the logarithm of mean monthly stock portfolio value, information in hours per week). In regressions (1) to (6), we consider all investors. In regressions (7) to (12), investors in the highest turnover quintile are excluded. Regressions (1) and (7) report the results for the respective subgroup of investors that has responded to the questionnaire without an overconfidence measure. In each of the following regressions we include one overconfidence variable (Overconfidence). Absolute value of t statistics are in parentheses. * indicates significance at 10%; ** indicates significance at 5%; *** indicates significance at 1%.

Dependent	(1) ln(Turnover)	(2) ln(Turnover)	(3) ln(Turnover)	(4) ln(Turnover)	(5) ln(Turnover)	(6) ln(Turnover)	(7) ln(Turnover)	(8) ln(Turnover)	(9) ln(Turnover)	(10) ln(Turnover)	(11) ln(Turnover)	(12) ln(Turnover)
	All respondents to the questionnaire						Highest turnover quintile excluded					
Overconfidence variable	-	misc	volest	volest (first group, before Sept 11)	bta1	bta2	-	misc	volest	volest (first group, before Sept 11)	bta1	bta2
Gender	-0.109	-0.327	0.224	0.129	0.270	0.283	-0.135	-0.685	-0.199	-0.442	-0.104	-0.081
	(0.24)	(0.50)	(0.41)	(0.20)	(0.54)	(0.58)	(0.36)	(1.46)	(0.50)	(0.93)	(0.28)	(0.22)
Age	-0.014	-0.014	-0.014	-0.018	-0.012	-0.011	-0.014	-0.016	-0.015	-0.015	-0.012	-0.009
	(1.48)	(1.08)	(1.38)	(1.32)	(1.26)	(1.13)	(1.84)*	(1.67)*	(2.04)**	(1.48)	(1.61)	(1.20)
Warrant trader	0.627	0.597	0.590	0.658	0.683	0.694	0.548	0.432	0.435	0.474	0.556	0.572
	(3.29)***	(2.32)**	(2.89)***	(2.58)**	(3.54)***	(3.61)***	(3.70)***	(2.43)**	(2.93)***	(2.54)**	(3.73)***	(3.92)***
High risk	0.373	0.275	0.418	0.605	0.405	0.387	0.193	0.167	0.046	0.208	0.230	0.259
	(1.18)	(0.66)	(1.19)	(1.42)	(1.28)	(1.23)	(0.71)	(0.53)	(0.15)	(0.52)	(0.83)	(0.96)
ln(Portfolio value)	-0.205	-0.126	-0.176	-0.112	-0.217	-0.230	-0.101	-0.051	-0.051	0.004	-0.105	-0.120
	(3.00)***	(1.37)	(2.34)**	(1.17)	(3.14)***	(3.31)***	(1.87)*	(0.80)	(0.91)	(0.05)	(1.95)*	(2.24)**
Information	-0.012	-0.007	-0.011	-0.017	-0.014	-0.017	0.000	0.002	-0.000	-0.001	-0.004	-0.010
	(0.78)	(0.41)	(0.75)	(0.68)	(0.90)	(1.11)	(0.04)	(0.15)	(0.02)	(0.04)	(0.39)	(0.86)
Overconfidence		0.521	0.086	0.055	0.210	0.400		0.530	0.160	0.150	0.243	0.528
		(1.05)	(0.65)	(0.32)	(0.80)	(1.53)		(1.51)	(1.69)*	(1.23)	(1.23)	(2.55)**
Constant	1.327	0.389	0.688	0.414	0.930	1.002	-0.107	-0.336	-0.514	-0.797	-0.164	-0.167
	(1.67)*	(0.33)	(0.76)	(0.36)	(1.14)	(1.24)	(0.17)	(0.39)	(0.78)	(0.92)	(0.26)	(0.27)
Observations	168	105	149	96	165	165	131	83	115	71	130	130
Adjusted R-squared	0.14	0.06	0.11	0.10	0.15	0.16	0.15	0.10	0.12	0.08	0.16	0.19

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