SONDERFORSCHUNGSBEREICH 504

Rationalitätskonzepte,
Entscheidungsverhalten und
ökonomische Modellierung

No. 03-07

Overconfidence and Trading Volume

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April 2003

Financial support from the Deutsche Forschungsgemeinschaft, SFB 504, at the University of Mannheim, is gratefully acknowledged.

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Comments welcome.

April 14, 2003

Abstract

Theoretical models predict that overconfident investors will trade more than rational investors. We directly test this hypothesis by correlating individual overconfidence scores with several measures of trading volume of individual investors (number of trades, turnover). Approximately 3000 online broker investors were asked to answer an internet questionnaire which was designed to measure various facets of overconfidence (miscalibration, the better than average effect, illusion of control, unrealistic optimism). The measures of trading volume were calculated by the trades of 215 individual investors who answered the questionnaire. We find that investors who think that they are above average in terms of investment skills or past performance trade more. Measures of miscalibration are, contrary to theory, unrelated to measures of trading volume. This result is striking 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. The results hold even when we control for several other determinants of trading volume in a cross-sectional regression analysis. In connection with other recent findings, we conclude that the usual way of motivating and modelling overconfidence which is mainly based on the calibration literature has to be treated with caution. We argue that our findings present 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.

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 February 2003 annualized turnover on the New York Stock Exchange (NYSE) was about 96 % and the daily number of shares traded on the NYSE in the year 2002 was about 1,440 million. The total value of trading on NYSE in the year 2002 was 10.3 trillion U.S. $.[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

[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.

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" literature and the "overconfidence" literature. 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". Modelling 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 psycholog-

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

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

ical 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.[8] 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".[9]

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?

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 3000 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

[8]We will discuss these further results in Section 3.1.

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

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 (modelled 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 modelling. 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."[10] 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. Closely related is the question whether the various overconfidence biases are related, i.e. whether the overconfidence scores are positively correlated. This is important for modelling as well. Usually, only one bias is incorporated into a model. Overconfidence models assume overestimation of the precision of information whereas this assumption is, besides the calibration literature, motivated by several other findings as well. However, it is by no means clear that these biases are related. Furthermore, we are able to test whether there is a psychological foundation of differences of opinion models by

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

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. Measures of miscalibration are, contrary to predictions of overconfidence models, unrelated to measures of trading volume. This result is striking 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). 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 modelling overconfidence which is based on the calibration literature has to be treated with caution. We argue that the "differences of opinion" literature better explains high levels of trading volume when compared to the "overconfidence" literature. Furthermore, our findings present 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 psychological and 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. 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 (2003) 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. They find an increase in trading activity after bull markets. This 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 (2002) 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. Kim and Nofsinger (2002) present evidence that Asian cultures are more prone to overconfidence than other cultures and therefore argue that studying Japanese investors “represents an excellent opportunity to assess and to identify the behavior of overconfident investors” (Kim and Nofsinger (2002), p. 2).

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, different cultures). 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. This can be done either empirically or experimentally. Our study uses the first approach and empirically tests the above mentioned hypothesis using field data. We directly measure overconfidence via a psychological online questionnaire for a group of individual investors with online broker accounts. So we *are* able to *directly* test the hypothesis that overconfidence leads to higher trading volume by correlating measures of overconfidence with the actual trading volume of the respective investor.

Our research is thus related to (the very few) studies in economics and finance that correlate psychological data (such as measures of overconfidence) with economic variables (such as trading volume).

Fenton-O’Creevy, Nicholson, Soane, and Willman (2000) analyze the link between psychological and economic variables empirically using data on the behavior of professional traders. They measure illusion of control, one manifestation of overconfidence that we will discuss more deeply in Section 3.1, 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.

Biais, Hilton, Mazurier, and Pouget (2002) use the second of the above mentioned approaches and analyze experimentally whether psychological traits and cognitive biases affect trading and performance. Based on the answers of 184 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 overconfident subjects have a greater tendency to place unprofitable orders. However, their overconfidence measure is unrelated to trading volume. Contrary to predictions of overconfidence models, overconfident subjects do not place more orders.

3 Overconfidence in the Psychological Literature and in Finance Models

3.1 Overconfidence in the Psychological Literature

In the psychological literature there is no precise definition of overconfidence. There are several findings that are often summarized as overconfidence. Under this view, which is the broadest possible that can be found in the literature, overconfidence can manifest itself in the following forms: miscalibration, the better than average effect, illusion of control, and unrealistic optimism. We will discuss these manifestations of overconfidence in turn.

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 large 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.

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)).

Illusion of control, and unrealistic optimism Langer (1975) defines illusion of control as "an expectancy of a personal success probability inappropriately higher than the objective probability would warrant".[11] Closely related is the phenomenon of unrealistic optimism about future life events (Weinstein (1980)). Presson and Benassi (1996) note in their survey and meta-analysis that after Langer's article was published, illusion of control "has become a catch phrase in studies in which researchers manipulate conditions that lead people to make nonveridical judgments of control, contingency, prediction ability, etc."[12] In other words, there is no precise definition of illusion of control in the psychological literature. Most of the illusion of control studies analyze how different manipulated variables such as choice, outcome sequence, task familiarity, or active involvement are related to illusion of control. Presson and Benassi (1996) stress that almost all studies do not measure the degree of control. Instead, most studies measure prediction ability or judgments of contingency so that Presson and Benassi (1996) suggest that the phrase "illusionary judgment" would better summarize the various operationalizations of illusion of control in the literature although they admit that "there is some question as to whether illusion of control researchers have examined a single underlying construct."[13]

The questions whether there are stable individual differences in the degree of overconfidence has long been unexplored. Recent psychological research tries to find out whether there are stable individual differences in reasoning or decision making competence (see Parker and Fischhoff (2000), Stanovich and West (1998), and Stanovich and West (2000)).

[11] Langer (1975), p. 311.

[12] Presson and Benassi (1996), p. 494.

[13] Presson and Benassi (1996), p. 502.

Furthermore, the question whether the above mentioned concepts - miscalibration, the better than average effect, illusion of control, and unrealistic optimism - are related is mainly unexplored. Some argue that these manifestations are related (see, for example, Taylor and Brown (1988), p. 194), others argue that this need not to be the case (see, for example, Biais, Hilton, Mazurier, and Pouget (2002), p. 9), or even deny a logical link (see, for example, Hvide (2002), p. 19). Most of the studies that analyze these various facets of overconfidence try to figure out which variables or stimuli induce overconfidence and under which circumstances overconfidence is reduced.[14] However, these studies do not analyze whether the above mentioned concepts are related.

3.2 Overconfidence in Finance Models

In this subsection, we will discuss the "differences of opinion" literature and the "overconfidence‘" literature more comprehensively.

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.

[14] See, for example, Presson and Benassi (1996), p. 505.

Differences of opinion are modelled 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 (2002), 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.

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* modelled as overestimation of the precision of private information. Assume there is a risky asset with liquidation value v which is a realization of $\tilde{v} \sim N(0, \sigma^2_{\tilde{v}})$. Investors receive private signals $\tilde{s} = \tilde{v} + c \cdot \tilde{e}$ with $\tilde{e} \sim N(0, \sigma^2_{\tilde{e}})$. It is assumed that $\tilde{v}$ and $\tilde{e}$ are independent such that $\tilde{s} \sim N(0, \sigma^2_{\tilde{v}} + c^2 \cdot \sigma^2_{\tilde{e}})$. If $c = 1$, investors are rational, if $0 \leq c < 1$, investors are overconfident. The conditional variance of $\tilde{v}$, given the realization s, is

$$Var[\tilde{v} \mid \tilde{s} = s] = Var(\tilde{v}) - \frac{(Cov[\tilde{v}, \tilde{s}])^2}{Var[\tilde{s}]} = \sigma^2_{\tilde{v}} - \frac{\sigma^4_{\tilde{v}}}{\sigma^2_{\tilde{v}} + c^2 \cdot \sigma^2_{\tilde{e}}} \qquad (1)$$

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. Benos (1998), Caballé and Sákovics (2003), Kyle and Wang (1997), Odean (1998b), and Wang (1998) incorporate this way of modelling 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).[15] 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 investors will trade more aggressively: The higher the degree of overconfidence of an investor, the higher her or his trading volume. Odean (1998) 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 is a form of heterogeneous 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

[15]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).

opinion are sometimes regarded as a form of of overconfidence, as described above.[16]

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 3000 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 3079 individual investors from a German online broker in the period from January 1997 to April 2001. We considered all investors that trade via internet, had opened their account prior to January 1997, had at least one transaction in 1997, and have an e-mail-address.[17] 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.[18] 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.

[16]The following example highlights 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).

[17]See Glaser (2003) for descriptive statistics and further details.

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

4.2 Design of the Study

All 3079 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.[19] We received the questionnaire data at the end of September, 2001, from the online broker.

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.[20] An investor who wants to buy a security has the choice between thousands of stocks whereas a sell decision only requires to analyze the usually very few stocks in the own portfolio (assuming that investors do not sell short). 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,

[19]See, for example, Graham and Harvey (2001).

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

the tendency to sell winners too early and ride losers too long.[21] 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)). 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. We compare various descriptive statistics of our whole sample with descriptive statistics of the subgroup of investors that has responded to the questionnaire (henceforth subgroup).

The median across subjects of the number of stock transactions of the whole sample is 54 and 52 for the subgroup over the 51 months from the beginning of January 1997 until the beginning of April 2001. Thus, the median number of stock market transactions is approximately one per month. The average number of stock transactions of the whole sample and the subgroup are 105 and 92, respectively. The median across subjects of the monthly average turnover is 33% in both groups. The median across subjects of the monthly average stock portfolio value is about 16,000 Euro in both groups whereas the mean is about 37,000 Euro in both groups. The median number of stocks in the portfolio

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

at the beginning of January 1999 (approximately the midpoint of the time period) is 5 in both groups. The mean and median age in both groups is about 40 years. In both groups, about 95 % of investors are male. Parametric and non-parametric tests show that there are no significant differences with regard to the above mentioned characteristics in the two groups of respondents and the remaining investors who have not responded to the questionnaire.[22] Thus, there is no indication of a sample selection bias.

4.4 Measures of Overconfidence

We consider the following forms of overconfidence: miscalibration, the better than average effect, illusion of control, and unrealistic optimism. 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. In designing the questionnaire we tried to be as close as possible to the concepts and experimental tasks in the psychological literature reviewed in Subsection 3.1. Of course, we were aware of the fact that this may lead to a lower response rate.

4.4.1 Miscalibration

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

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).

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

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.[23] 137 of 215 Investors answered at least one question. 114 investors answered all questions.[24]

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 %. Table 1 summarizes the results. We use the abbreviation OC for the miscalibration scores as overconfidence models assume that investors are miscalibrated. 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.[25]

Stock Market Forecasts The investors were asked to provide upper and lower bounds of 90 % confidence intervals to five questions concerning stock market forecasts (Deutscher

[23] See, for example, Klayman, Soll, Gonzáles-Vallejo, and Barlas (1999), and Biais, Hilton, Mazurier, and Pouget (2002) and Subsection 3.1.

[24] 7 Investors answered 1 question, 3 investors answered 2 questions, 4 Investors answered 3 questions, and 9 Investors answered 4 questions.

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

Aktienindex DAX, Nemax50 Performance Index, three German Stocks) for the end of the year 2001.[26] The use of confidence interval questions is widely used to elicit subjects probability distributions, perceptions of expected returns, and variance estimations of stock returns.[27]

190 of 215 Investors answered at least one question. 165 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. Again, Table 1 summarizes the results.[29] The results are similar to prior research that finds percentages of surprises on exchange rate and stock price predictions from 71 % to 83 %.[30].

4.4.2 Better than Average Effect

We try to 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 costumers of your discount brokerage house have better skills

[26]The respondents to the first questionnaire had a forecast horizon of 21 weeks, respondents to the second questionnaire had a 14 week horizon.

[27]See, for example, Graham and Harvey (2001) and Siebenmorgen and Weber (2001) for a discussion.

[28]4 Investors answered 1 question, 6 investors answered 2 questions, 5 Investors answered 3 questions, and 10 Investors answered 4 questions.

[29]This overconfidence measure is the only one which could be reasonably affected by the different time horizons and the terror attacks of September, 11th. Respondents to the second questionnaire have a lower percentage of surprises. This difference is only marginally significant ($p = 0.0947$). See Glaser and Weber (2003) for further details.

[30]See Hilton (2001), p. 42

(e.g. in the way you 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 costumers of your discount brokerage house had higher returns than you in the four-year period from January 1997 to December 2000? (Please give a number between 0 % and 100 %)

Table 1 summarizes the results of the answers to these two questions. 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 ($\mathrm{BTA1}_i$ and $\mathrm{BTA2}_i$) as $\frac{50-\mathrm{answer}_i}{50}$ as well as the arithmetic average of these two scores ($\mathrm{BTA3}_i$). These ratios yield 0 if the respondent thinks she or he is average, 1 if she or he thinks is better than everybody else, and -1 if she or he thinks 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. The high standard deviations are signs of large individual differences.

4.4.3 Illusion of Control and Unrealistic Optimism

We consider the following aspects that are mainly summarized as illusion of control as described in Subsection 3.1: control over (an almost) random task (such as investing in the stock market), unrealistically high personal success probability, and unrealistic optimism about the future. Nevertheless, we use the term illusion of control for all these conceptualizations in the following.

We calculate three illusion of control scores. The first illusion of control score is based on the answers to the following four statements. Investors were asked to state scores from 1 (I totally agree) to 5 (I completely disagree). For each question we calculate an illusion of control score of investor i as described below the respective statement.

1) I never buy stocks that will underperform in the future.

   $\mathrm{I1}_i = \frac{5-\mathrm{Answer}_i}{4}$. If the investor thinks she or he will never buy stocks that will underperform in the future, the score I1 is 100 %. If the investor completely disagrees, the score is 0 %.

2) I am not able to identify stocks with above average performance in the future.

   $\mathrm{I2}_i = \frac{\mathrm{Answer}_i-1}{4}$. If the investor thinks she or he is not able to identify stocks with above average performance in the future, the score I2 is 0 %.

3) Buying stocks is like buying lottery tickets. Above-average performance seems to me to be more a matter of chance.

   $\mathrm{I3}_i = \frac{\mathrm{Answer}_i-1}{4}$. If the investor thinks buying stocks is like buying lottery tickets, the score I3 is 0 %.

4) My forecasts of future stock prices are always true.

   $\mathrm{I4}_i = \frac{5-\mathrm{Answer}_i}{4}$. If the respondent thinks her or his forecasts are always true, the score I4 is 100 %.

$\mathrm{IC1}_i$ is the arithmetic average of these four scores.

We also asked the investors to give an estimate of their portfolio performance in the past (from January 1997 to December 2000). After that, the investors were asked to forecast the return of their portfolio in the following four-year period (from January 2001 to

December 2004). The next illusion of control score is based on these estimations of the past performance and the future performance. The score of investor i, $i = 1, \ldots, 215$, is calculated as follows: $\mathrm{IC2}_i = \frac{\text{Future Performance}_i - \text{Past Performance}_i}{\max\limits_{i=1,\ldots,215} |\text{Future Performance}_i - \text{Past Performance}_i|}$.

The third illusion of control score IC3 is based on the comparison of the 2001 judgment of the portfolio performance in the year 2001 and the judgment of the performance of the Deutsche Aktienindex DAX in the same period. The score is calculated as follows: $\mathrm{IC3}_i = \frac{\text{Portfolio Performance}_i - \text{DAX Performance}_i}{\max\limits_{i=1,\ldots,215} |\text{Portfolio Performance}_i - \text{DAX Performance}_i|}$

Table 1 presents summary statistics of these three scores. We find that the median person has illusion of control scores at approximately the midpoint of the respective interval. The median investor thinks her or his performance in the future will be lower than the performance in the past (IC2) and that the performance of her or his performance in the year 2001 will be as high as the performance of the Deutsche Aktienindex DAX (IC3). However, the high standard deviations indicate large individual differences.

4.4.4 Correlation of Overconfidence Measures

Table 2 presents correlation coefficients of seven 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. To conserve space we skip the variables OC3 and BTA3 which are arithmetic averages of OC1 and OC2 or BTA1 and BTA2, respectively.

The two miscalibration scores, OC1 and OC2, are significantly positively correlated ($p = 0.0568$). Although knowledge questions and stock market prediction questions are completely different tasks this result suggests internal validity of the two calibration concepts. The two better than average scores, BTA1 and BTA2, have a correlation coefficient of 0.6786 ($p = 0.0000$). 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. The two illusion of control scores, IC2 and IC3, are positively correlated at the 10 % level. This positive correlation seems plausible given that in these two tasks estimation of portfolio performance or stock market performance are involved. On average, investors who think that their future four year performance will be higher than their past four year performance do believe that their own portfolio performance in the year 2001 will be higher than the performance of the German blue chip index DAX. Surprisingly, IC1 and IC3 are significantly negatively correlated. The higher the IC1 score the more people believe that they can control or predict the market. The negative correlation of IC1 and IC3 indicates that people who believe that they can predict the market think that their 2001 portfolio performance will be lower than the 2001 performance of the German blue chip index. We do not have a plausible explanation for this negative correlation. To summarize, miscalibration and the better than average effect seem to be stable individual traits whereas our scores IC1, IC2, and IC3 question whether illusion of control is a single underlying construct which is in line with Presson and Benassi (1996). Most correlations between scores of the various facets of overconfidence are insignificant. Some are even negative. The correlation between OC2 and IC3 is significantly positive at the 1 % level. This might be explained by the the fact that in both tasks stock market predictions are involved. The higher the percentage of surprises in stock market forecasts, the more an investor believes that her or his portfolio performance will be higher than the German market index DAX. The correlation coefficients between IC1 and both better than average scores are significantly negative at the 1 % level. Investors who think that they are above average in terms of investment skills or past performance have a greater tendency to think that the stock market is unpredictable. We do not have an explanation for this perhaps surprising result.

Furthermore, we find simultaneous over- and underconfidence. According to the calibration questions all investors are overconfident, whereas the median answer to the better than average questions is 50 %. Kirchler and Maciejovsky (2002) find similar results. They investigate individual overconfidence in the context of an experimental asset market with several periods. Before each period, overconfidence was measured. Participants were asked to state subjective confidence intervals for the price of the single risky asset in the next trading period as well as their subjective certainty. They also find simultaneous over- and underconfidence. Depending on the method overconfidence was measured - subjective confidence intervals on the one hand and the comparison of objective accuracy and subjective certainty on the other - some participants can be classified as either overconfident or underconfident.

5 Overconfidence and Trading Volume: Empirical Results

This section presents the results on the correlation of our nine overconfidence measures and three measures of trading volume. Subsection 5.1 presents correlation coefficients, Subsection 5.2 presents cross-sectional regression results.

5.1 Overconfidence and Trading Volume: Correlation Coefficients

Table 3 presents correlation coefficients of 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 nine overconfidence measures described in Section 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.[31] The first half of the table presents correlation coefficients for all investors who have responded to the questionnaire. In the second half, investors in the highest turnover quintile are excluded.

Focusing on the first half of Table 3 shows, that overconfidence as measured by calibration questions is, contrary to theory, *negatively* correlated with the logarithm of the number of stock market transactions and the logarithm of the number of stock market purchases. However, these correlations are insignificant. The better than average scores are significantly positively correlated with the number of stock market transactions and the number of stock purchases. The illusion of control scores are not significantly correlated with the three measures of trading volume.

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

[31]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 heteroskedasticity in the cross-sectional regression analysis in Subsection 5.2. See Spanos (1986), chapter 21, especially, pp. 455-456, Davidson and McKinnon (1993), chapter 14, and Atkinson (1985), pp. 80-81. We therefore use the natural logarithm of the above mentioned variables when calculating correlation coefficients.

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 effect of overconfidence is swamped. Therefore, the second half of Table 3 shows the results when investors in the highest turnover quintile are excluded. As hypothesized, the effect of overconfidence as measured by the better than average scores BTA1, BTA2, and BTA3 are stronger. Eight out of nine correlation coefficients are positive at least at the 5 % level. Three correlation coefficients are significantly positive at the 1 % level. Most of the correlations between miscalibration scores and measures of trading volume remain insignificant with two exceptions. OC1 and the number of stock market purchases are now *negatively* correlated and OC3 and turnover are positive correlated at the 10 % level.

As overconfidence models do not predict that overconfidence is the single determinant of trading volume and as overconfidence measures might be correlated with other determinants of trading volume we analyze the explanatory power of our overconfidence measures in multiple regressions in the next subsection.

5.2 Overconfidence and Trading Volume: Cross-Sectional Regressions

Table 5 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). Table 4 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 studies that overconfidence or illusion of control increase with the level of active involvement in a task.[32] We regard the information variable as a proxy for the level of involvement in the task of investing or trading. The first regression reports the results for the subgroup of investors that has responded to the questionnaire without an overconfidence measure as explanatory variable. In each of the nine following regressions we include one overconfidence variable (Overconfidence). Only two overconfidence measures are significantly positively related to the number of stock market transactions at the 5 % level and the 10 % level, BTA1 and BTA3. Investors who assess their skills as above average trade more stocks. However, miscalibrated investors and investors prone to the illusion of control 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.[33]

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 6 presents regression results on the relation between the logarithm of the number of stock market purchases and several explanatory variables. Both BTA1 and BTA3 are significant at the 5 % level with the expected sign. The t-values are,

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

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

as hypothesized, higher than in Table 5.

Table 7 presents regression results on the relation between the logarithm of mean monthly turnover and several explanatory variables. None of the nine overconfidence measures are significantly related to turnover. 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.

As in Section 5.1, we now exclude investors in the highest turnover quintile and run the regressions just presented for the remaining investors. Table 8, Table 9, and Table 10 show the results. As predicted, the effect of overconfidence is much stronger. The better than average scores are significantly positive at least at the 5 % level (the only exception is regression (5) in Table 10). The miscalibration and illusion of control scores have no significant impact and the signs of the coefficients are, contrary to theory, mainly negative. Furthermore, the adjusted R-squared values in Table 8, Table 9, and Table 10 are higher than in the respective table 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 Table 8, Table 9, and Table 10 are higher when the better than average scores are included when compared to the respective regression (1) 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 than in the three tables that analyze all respondents to the questionnaire suggesting, again, that the accounts with the highest turnover values might be entertainment accounts.

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 nine 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.

6 Discussion

Table 11 summarizes our findings. We show that overconfidence as measured by calibration questions is negatively related to the number of trades. This result is inconsistent with theory but consistent with findings of Biais, Hilton, Mazurier, and Pouget (2002). Thus, the finding seems to be robust. 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 (2002) and our study are the only exceptions that analyze this link. Overconfidence models are motivated by psychological studies which show that people are generally miscalibrated or by empirical findings that are consistent with miscalibrated investors, such as high trading volume. But there might be other biases that are able to explain the same empirical findings when implemented in a theoretical model. But theoretical models often incorporate only one behavioral bias. We are able to test whether different forms of overconfidence have different effects on trading volume. Information on this issue is essential for modelling purposes because we are able to rule out some forms of overconfidence as the main driving forces of trading volume which are therefore inappropriate as assumptions in theoretical models. This 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. Scores of miscalibration obviously fail to explain trading volume.

Furthermore, there are other reasons that might explain this failure of miscalibration scores in explaining volume. In the psychological literature, there is a large debate 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)). In other words: The way investors are asked to state, say, the future performance of a stock, might influence the result of whether confidence intervals are too narrow or, perhaps, well calibrated. If miscalibration is not a stable individual trait or if the degree of miscalibration depends on a specific task then it is no surprise that we are unable to empirically confirm the hypothesis that a higher degree of miscalibration leads to higher trading volume.

Moreover, according to the usual interpretation of overconfidence measures based on calibration questions *all* investors are overconfident. Section 4.3 shows that investors in our sample trade a lot when compared to similar studies.[34] It may be possible that *all* in-

[34]Odean (1999), for example, analyzes trades of 10,000 accounts from January 1987 to December 1993. The trades file has 162,948 records in this seven year period (0.2 trades per investor per month). Our data set consists of 563,104 trades

vestors in our data set are overconfident and thus, *all* traders trade more than "normal" investors (which are not included in our data set). This interpretation is consistent with Barber and Odean (2002) who argue that online investors are *generally* overconfident and active traders. They analyze trading volume and performance of a group of 1,600 investors who switched from phone-based to online trading during the sample period. They find that trading volume increases and performance decreases after going online. They thus conclude that "overconfident investors were more likely to go online and once online the illusion of control and the illusion of knowledge further increased their overconfidence. Overconfidence led them to trade actively...".[35] Note that we only consider investors in our sample who trade online. The Barber and Odean (2002) argument is, however, not in line with the large variation across individuals of the number of trades in our data set. It is *not* true that *all* investors in our sample trade a lot.

Our results concerning overconfidence as measured by the better than average effect are very promising. We find that investors who think that they are above average do trade more. This finding 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 (2002), 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

of 3079 over a period of only 51 months (3.5 trades per investor per month). Note, however, the different time periods.

[35] Barber and Odean (2002), p. 479.

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)".[36] 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."[37].

Why do "overconfidence" models break down when they are confronted with studies that link miscalibration scores and the number of trades? Why are "differences of opinion" perhaps a better way of explaining high levels of trading volume? In both types of models, investors often receive noisy signals which are the sum of two random variables: the value of the risky asset and a random error term. Loosely speaking, "differences of opinion" models assume that investors disagree about means of random variables whereas investors in "overconfidence" models disagree about variances. Perhaps, modelling disagreement about mean returns has a better foundation in documented investor behavior and investor expectations than disagreement about the variance of returns. Glaser and Weber (2003) find evidence that is consistent with this conjecture. Disagreement with regard to return forecasts is higher than disagreement with regard to volatility forecasts for this group of

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

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

individual investors.

Besides mentioning the strengths of our approach - the ability to directly test the hypotheses that a higher degree of overconfidence leads to higher trading volume - we want to discuss some possible weaknesses as well. We assume that the overconfidence scores are stable individual traits and are constant over time. This is in line with most overconfidence models mentioned in Subsection 3.2. However, psychological evidence on this issue is not unequivocal, as discussed above. Unfortunately, we were not able to verify whether our overconfidence scores are constant over time. A closely related point is that our overconfidence measures were obtained after the 51 months time period that was used to calculate the measures of trading volume of the respective investors. Another possible weakness might be the fact that we conduct 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 (2002) 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.

7 Conclusion

The contribution of this paper is to measure overconfidence of a group of online broker investors in various dimensions (miscalibration, the better than average effect, illusion of control, unrealistic optimism) 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. Biais, Hilton, Mazurier, and Pouget (2002) underline "the importance of specifying what kind of overconfidence - miscalibration, the better than average effect, illusion of control - may be influencing trading behavior" (p. 16). This view coincides with Hirshleifer (2001) who 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."[38]. We are able to contribute to this endeavor.

We find that investors who think that they are above average trade more. 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 (2002) 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 modelling overconfidence which is mainly based on the calibration literature has to be treated with caution. We argue that our findings present a psychological foundation for the differences of opinion explanation of high levels of trading volume.

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

There are several suggestions for future research. We measure various facets of overconfidence: miscalibration, the better than average effect, illusion of control, and unrealistic optimism. 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 to 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 modelling. Last but but least, future overconfidence models should assume "differences of opinion" but this "differences of opinion" should *not* be a result of overestimation of the precision of information.

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Table 1: **Overconfidence Variables: Descriptive Statistics**

This table presents descriptive statistics of the overconfidence measures defined in Subsection 4.4 as well as the intervals that contain the respective measures. For all overconfidence measures a higher value indicates a higher degree of overconfidence. The table presents mean, median, standard deviation (std.dev.), and the number of investors who responded to the respective question (no. Obs.).

Miscalibration		Interval	Mean of % of surprises	Median of % of surprises	std.dev of % of surprises	No.Obs.
	General Knowledge Questions (OC1)	$\in$ [0 %,100 %]	75 %	80 %	24 %	137
	Stock Market Forecasts (OC2)	$\in$ [0 %,100 %]	61 %	60 %	32 %	190
	All Questions (OC3)	$\in$ [0 %,100 %]	67 %	70 %	21 %	137
Better than average effect			**Mean**	**Median**	**std.dev**	**No.Obs**
	Question 1	$\in$ [0,100]	43.82	50	18.42	212
	Question 2	$\in$ [0,100]	46.99	50	19.33	212
	BTA1	$\in$ [-1,1]	0.12	0	0.37	212
	BTA2	$\in$ [-1,1]	0.06	0	0.39	212
	BTA3	$\in$ [-1,1]	0.09	0	0.35	212
Illusion of control and unrealistic optimism			**Mean**	**Median**	**std.dev**	**No.Obs**
	IC1	$\in$ [0,1]	0.46	0.50	0.16	215
	IC2	$\in$ [-1,1]	-0.02	-0.02	0.14	206
	IC3	$\in$ [-1,1]	-0.11	0.00	0.25	188

Table 2: **Correlation of Overconfidence Variables**

This table presents pairwise correlations between seven of 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. To conserve space we skip the variables OC3 and BTA3 which are arithmetic averages of OC1 and OC2 or BTA1 and BTA2, respectively. * indicates significance at 10%; *** indicates significance at 1%.

	OC1	OC2	BTA1	BTA2	IC1	IC2	IC3
OC1	1 137						
OC2	0.1631 (0.0568)* 137	1 190					
BTA1	-0.0402 (0.6411) 137	-0.0867 (0.2345) 190	1 212				
BTA2	0.1487 (0.0828)* 137	-0.0058 (0.9363) 190	0.6785 (0.0000)*** 212	1 212			
IC1	-0.0513 (0.5516) 137	-0.0234 (0.7491) 190	-0.2241 (0.0010)*** 212	-0.1865 (0.0065)*** 212	1 215		
IC2	-0.0454 (0.6021) 134	0.0828 (0.2612) 186	-0.0902 (0.1994) 204	-0.2024 (0.0037)*** 204	0.0604 (0.3883) 206	1 206	
IC3	-0.0153 (0.8602) 135	0.2342 (0.0013)*** 186	0.0485 (0.5082) 188	0.1134 (0.1212) 188	-0.1915 (0.0085)*** 188	0.1385 (0.0594)* 186	1 188

Table 3: **Correlation of Overconfidence Measures and Measures of Trading Volume**

This table presents correlation coefficients of 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 nine 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. Turnover is calculated as the average monthly turnover from January 1997 until April 2001. The first half of the table presents correlation coefficients for all investors that have responded to the questionnaire. In the second half, investors in the highest turnover quintile are excluded. * indicates significance at 10%; ** indicates significance at 5%; *** indicates significance at 1%.

		OC1	OC2	OC3	BTA1	BTA2	BTA3	IC1	IC2	IC3
Respondents to the questionnaire	ln(Number of stock market transactions)	-0.1341 (0.1283) 130	-0.0174 (0.8166) 180	-0.0846 (0.3384) 130	0.1555 (0.0272)** 202	0.1348 (0.0559)* 202	0.1588 (0.0240)** 202	-0.0125 (0.8593) 205	-0.0206 (0.7742) 196	0.0821 (0.2758) 178
	ln(Number of stock market purchases)	-0.1410 (0.1109) 129	-0.0074 (0.9213) 179	-0.0914 (0.3028) 129	0.1320 (0.0624)* 200	0.1204 (0.0894)* 200	0.1386 (0.0503)* 200	-0.0144 (0.8383) 203	0.0214 (0.7675) 194	0.0735 (0.3308) 177
	ln(Turnover)	0.0612 (0.4963) 126	0.0716 (0.3461) 175	0.0867 (0.3342) 126	0.0196 (0.7846) 196	0.0693 (0.3345) 196	0.0496 (0.4903) 196	0.0606 (0.3949) 199	-0.0066 (0.9285) 190	0.0439 (0.5666) 173
Highest turnover quintile excluded	ln(Number of stock market transactions)	-0.1593 (0.1028) 106	-0.0872 (0.2986) 144	-0.1358 (0.1652) 106	0.2151 (0.0055)*** 165	0.1817 (0.0195)** 165	0.2167 (0.0052)*** 165	-0.0438 (0.5752) 166	-0.0142 (0.8593) 159	0.0384 (0.6474) 144
	ln(Number of stock market purchases)	-0.1653 (0.0919)* 105	-0.0768 (0.3617) 143	-0.1382 (0.1596) 105	0.1891 (0.0156)** 163	0.1611 (0.0399)** 163	0.1920 (0.0141)** 163	-0.0287 (0.7155) 164	0.0362 (0.6525) 157	0.0228 (0.7871) 143
	ln(Turnover)	0.1490 (0.1350) 102	0.0679 (0.4272) 139	0.1906 (0.0550)* 102	0.0906 (0.2560) 159	0.2079 (0.0085)*** 159	0.1644 (0.0384)** 159	-0.0850 (0.2853) 160	-0.0978 (0.2290) 153	0.0855 (0.3170) 139

Table 4: **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 al 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.
OC1	Questionnaire	Percentage of surprises in knowledge questions.
OC2	Questionnaire	Percentage of surprises in stock market predictions.
OC3	Questionnaire	Arithmetic average of OC1 and OC2.
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.
BTA3	Questionnaire	Arithmetic average of BTA1 and BTA2.
IC1	Questionnaire	Illusion of control score based on the level of agreement with four statements.
IC2	Questionnaire	Illusion of control score based on the estimation of own past and future four-year-performance.
IC3	Questionnaire	Illusion of control score based on the estimation of the return of the German stock market and own portfolio return in 2001.

Table 5: **The Number of Stock Market Transactions and Measures of Overconfidence: Cross-Sectional Regressions (All Respondents to the Questionnaire)**

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). The first regression reports the results for the subgroup of investors that has responded to the questionnaire without an overconfidence measure. In each of the nine 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)
Overconfidence variable	-	OC1	OC2	OC3	BTA1	BTA2	BTA3	IC1	IC2	IC3
Gender	0.082	-0.425	-0.156	-0.456	0.233	0.212	0.230	0.073	0.210	-0.206
	(0.22)	(0.87)	(0.34)	(0.93)	(0.58)	(0.52)	(0.57)	(0.19)	(0.51)	(0.45)
Age	-0.007	-0.012	-0.006	-0.012	-0.005	-0.005	-0.004	-0.007	-0.005	-0.006
	(0.82)	(1.20)	(0.68)	(1.14)	(0.63)	(0.56)	(0.56)	(0.88)	(0.65)	(0.67)
Warrant trader	0.850	0.797	0.855	0.801	0.882	0.885	0.887	0.850	0.841	0.813
	(5.46)***	(4.13)***	(5.04)***	(4.14)***	(5.60)***	(5.57)***	(5.62)***	(5.45)***	(5.26)***	(4.83)***
High risk	-0.207	-0.166	-0.229	-0.176	-0.181	-0.215	-0.201	-0.208	-0.221	-0.228
	(0.84)	(0.55)	(0.84)	(0.58)	(0.74)	(0.87)	(0.82)	(0.84)	(0.84)	(0.84)
ln(Portfolio value)	0.524	0.538	0.551	0.538	0.518	0.511	0.511	0.527	0.512	0.539
	(9.55)***	(7.89)***	(9.10)***	(7.85)***	(9.36)***	(9.07)***	(9.18)***	(9.57)***	(9.04)***	(8.96)***
Information	-0.004	-0.006	-0.005	-0.006	-0.012	-0.009	-0.012	-0.002	-0.005	-0.007
	(0.35)	(0.46)	(0.36)	(0.45)	(0.96)	(0.71)	(0.94)	(0.17)	(0.42)	(0.56)
Overconfidence		-0.359	0.100	-0.170	0.447	0.295	0.452	0.348	-0.669	0.278
		(0.97)	(0.40)	(0.40)	(2.11)**	(1.39)	(1.93)*	(0.71)	(1.01)	(0.84)
Constant	-1.296	-0.441	-1.394	-0.589	-1.474	-1.389	-1.422	-1.466	-1.362	-1.125
	(2.02)**	(0.50)	(1.87)*	(0.64)	(2.24)**	(2.09)**	(2.16)**	(2.14)**	(2.02)**	(1.53)
Observations	171	107	152	107	168	168	168	171	163	150
Adjusted R-squared	0.41	0.43	0.41	0.43	0.42	0.41	0.42	0.41	0.40	0.41

Table 6: **The Number of Stock Market Purchases and Measures of Overconfidence: Cross-Sectional Regressions (All Respondents to the Questionnaire)**

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). The first regression reports the results for the subgroup of investors that has responded to the questionnaire without an overconfidence measure. In each of the nine 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)
Overconfidence variable	-	OC1	OC2	OC3	BTA1	BTA2	BTA3	IC1	IC2	IC3
Gender	0.067	-0.332	-0.124	-0.363	0.207	0.189	0.206	0.062	0.185	-0.173
	(0.19)	(0.72)	(0.29)	(0.78)	(0.54)	(0.49)	(0.54)	(0.17)	(0.48)	(0.40)
Age	-0.010	-0.014	-0.008	-0.013	-0.008	-0.008	-0.008	-0.010	-0.009	-0.008
	(1.31)	(1.49)	(1.00)	(1.41)	(1.10)	(1.02)	(1.02)	(1.35)	(1.12)	(0.99)
Warrant trader	0.788	0.732	0.810	0.738	0.821	0.825	0.827	0.788	0.780	0.761
	(5.37)***	(4.01)***	(5.06)***	(4.02)***	(5.54)***	(5.52)***	(5.56)***	(5.35)***	(5.16)***	(4.79)***
High risk	-0.065	0.018	-0.033	0.019	-0.031	-0.068	-0.051	-0.066	-0.038	-0.056
	(0.27)	(0.06)	(0.12)	(0.06)	(0.13)	(0.28)	(0.22)	(0.28)	(0.15)	(0.21)
ln(Portfolio value)	0.524	0.539	0.553	0.540	0.516	0.508	0.509	0.525	0.509	0.538
	(10.06)***	(8.28)***	(9.62)***	(8.23)***	(9.85)***	(9.54)***	(9.66)***	(10.04)***	(9.46)***	(9.39)***
Information	0.002	-0.000	0.003	0.000	-0.006	-0.003	-0.006	0.003	0.001	-0.000
	(0.17)	(0.00)	(0.21)	(0.03)	(0.50)	(0.27)	(0.50)	(0.27)	(0.09)	(0.03)
Overconfidence		-0.390	0.172	-0.130	0.441	0.317	0.462	0.199	-0.625	0.211
		(1.11)	(0.73)	(0.32)	(2.21)**	(1.59)	(2.10)**	(0.43)	(1.00)	(0.68)
Constant	-1.693	-0.985	-1.968	-1.192	-1.856	-1.770	-1.804	-1.791	-1.735	-1.632
	(2.79)***	(1.18)	(2.80)***	(1.38)	(2.99)***	(2.83)***	(2.91)***	(2.76)***	(2.73)***	(2.35)**
Observations	170	106	151	106	167	167	167	170	162	149
Adjusted R-squared	0.43	0.45	0.44	0.45	0.44	0.43	0.44	0.43	0.42	0.43

Table 7: **Turnover and Measures of Overconfidence: Cross-Sectional Regressions (All Respondents to the Questionnaire)**

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). The first regression reports the results for the subgroup of investors that has responded to the questionnaire without an overconfidence measure. In each of the nine 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(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)
Overconfidence variable	-	OC1	OC2	OC3	BTA1	BTA2	BTA3	IC1	IC2	IC3
Gender	-0.109	-0.327	0.230	-0.284	0.270	0.283	0.284	-0.125	0.309	0.154
	(0.24)	(0.50)	(0.42)	(0.44)	(0.54)	(0.58)	(0.57)	(0.27)	(0.62)	(0.28)
Age	-0.014	-0.014	-0.014	-0.015	-0.012	-0.011	-0.012	-0.015	-0.014	-0.017
	(1.48)	(1.08)	(1.41)	(1.12)	(1.26)	(1.13)	(1.19)	(1.58)	(1.46)	(1.63)
Warrant trader	0.627	0.597	0.589	0.589	0.683	0.694	0.690	0.629	0.647	0.549
	(3.29)***	(2.32)**	(2.89)***	(2.28)**	(3.54)***	(3.61)***	(3.58)***	(3.30)***	(3.33)***	(2.68)***
High risk	0.373	0.275	0.448	0.294	0.405	0.387	0.401	0.370	0.520	0.491
	(1.18)	(0.66)	(1.28)	(0.69)	(1.28)	(1.23)	(1.27)	(1.17)	(1.54)	(1.40)
ln(Portfolio value)	-0.205	-0.126	-0.180	-0.124	-0.217	-0.230	-0.224	-0.200	-0.217	-0.189
	(3.00)***	(1.37)	(2.42)**	(1.34)	(3.14)***	(3.31)***	(3.23)***	(2.92)***	(3.09)***	(2.52)**
Information	-0.012	-0.007	-0.010	-0.006	-0.014	-0.017	-0.017	-0.008	-0.012	-0.014
	(0.78)	(0.41)	(0.68)	(0.35)	(0.90)	(1.11)	(1.08)	(0.50)	(0.81)	(0.92)
Overconfidence		0.521	0.207	0.381	0.210	0.400	0.373	0.660	-0.795	0.465
		(1.05)	(0.68)	(0.67)	(0.80)	(1.53)	(1.29)	(1.11)	(0.98)	(1.12)
Constant	1.327	0.389	0.681	0.476	0.930	1.002	0.954	1.007	1.014	1.147
	(1.67)*	(0.33)	(0.75)	(0.39)	(1.14)	(1.24)	(1.18)	(1.19)	(1.23)	(1.28)
Observations	168	105	149	105	165	165	165	168	160	147
Adjusted R-squared	0.14	0.06	0.11	0.06	0.15	0.16	0.16	0.14	0.15	0.12

Table 8: **The Number of Stock Market Transactions and Measures of Overconfidence: Cross-Sectional Regressions (Investors in Highest Turnover Quintile Excluded)**

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). Investors in the highest turnover quintile are excluded. The first regression reports the results for the subgroup of investors that has responded to the questionnaire without an overconfidence measure. In each of the nine 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)
Overconfidence variable	-	OC1	OC2	OC3	BTA1	BTA2	BTA3	IC1	IC2	IC3
Gender	0.206	-0.337	-0.185	-0.364	0.279	0.263	0.285	0.202	0.235	-0.193
	(0.50)	(0.62)	(0.39)	(0.67)	(0.69)	(0.64)	(0.70)	(0.49)	(0.56)	(0.40)
Age	-0.006	-0.009	-0.006	-0.008	-0.003	-0.002	-0.002	-0.006	-0.006	-0.006
	(0.75)	(0.82)	(0.69)	(0.73)	(0.41)	(0.22)	(0.22)	(0.71)	(0.75)	(0.65)
Warrant trader	0.768	0.662	0.735	0.666	0.782	0.797	0.794	0.768	0.757	0.768
	(4.72)***	(3.23)***	(4.12)***	(3.25)***	(4.88)***	(4.93)***	(4.96)***	(4.70)***	(4.50)***	(4.36)***
High risk	-0.382	-0.178	-0.503	-0.187	-0.315	-0.349	-0.322	-0.378	-0.507	-0.577
	(1.37)	(0.52)	(1.55)	(0.54)	(1.15)	(1.27)	(1.18)	(1.35)	(1.65)	(1.77)*
ln(Portfolio value)	0.561	0.530	0.586	0.531	0.552	0.543	0.545	0.561	0.558	0.591
	(9.74)***	(7.36)***	(9.19)***	(7.35)***	(9.73)***	(9.44)***	(9.59)***	(9.71)***	(9.33)***	(9.24)***
Information	0.006	0.000	0.003	-0.001	-0.005	-0.004	-0.007	0.005	0.005	0.005
	(0.53)	(0.01)	(0.22)	(0.04)	(0.40)	(0.31)	(0.54)	(0.43)	(0.44)	(0.37)
Overconfidence		-0.391	-0.131	-0.297	0.571	0.523	0.669	-0.198	-0.455	0.097
		(0.97)	(0.49)	(0.68)	(2.70)***	(2.35)**	(2.80)***	(0.40)	(0.70)	(0.29)
Constant	-1.963	-0.682	-1.680	-0.793	-2.084	-2.017	-2.069	-1.877	-1.941	-1.825
	(2.92)***	(0.70)	(2.19)**	(0.80)	(3.15)***	(3.04)***	(3.14)***	(2.65)***	(2.78)***	(2.38)**
Observations	134	85	118	85	133	133	133	134	128	118
Adjusted R-squared	0.47	0.43	0.47	0.43	0.49	0.48	0.49	0.46	0.45	0.47

Table 9: **The Number of Stock Market Purchases and Measures of Overconfidence: Cross-Sectional Regressions (Investors in Highest Turnover Quintile Excluded)**

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). Investors in the highest turnover quintile are excluded. The first regression reports the results for the subgroup of investors that has responded to the questionnaire without an overconfidence measure. In each of the nine 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)
Overconfidence variable	-	OC1	OC2	OC3	BTA1	BTA2	BTA3	IC1	IC2	IC3
Gender	0.177	-0.243	-0.156	-0.269	0.253	0.239	0.261	0.172	0.203	-0.151
	(0.45)	(0.47)	(0.34)	(0.52)	(0.66)	(0.62)	(0.68)	(0.44)	(0.50)	(0.33)
Age	-0.009	-0.011	-0.007	-0.009	-0.006	-0.004	-0.004	-0.009	-0.009	-0.007
	(1.16)	(1.04)	(0.87)	(0.92)	(0.78)	(0.55)	(0.57)	(1.11)	(1.12)	(0.82)
Warrant trader	0.699	0.602	0.689	0.611	0.715	0.732	0.728	0.699	0.687	0.703
	(4.51)***	(3.09)***	(4.04)***	(3.11)***	(4.71)***	(4.78)***	(4.81)***	(4.50)***	(4.27)***	(4.18)***
High risk	-0.183	0.108	-0.200	0.111	-0.097	-0.129	-0.098	-0.178	-0.234	-0.330
	(0.67)	(0.31)	(0.61)	(0.32)	(0.36)	(0.48)	(0.37)	(0.65)	(0.76)	(1.00)
ln(Portfolio value)	0.546	0.510	0.574	0.511	0.535	0.524	0.526	0.546	0.539	0.577
	(9.88)***	(7.33)***	(9.35)***	(7.30)***	(9.86)***	(9.54)***	(9.70)***	(9.85)***	(9.37)***	(9.36)***
Information	0.010	0.004	0.008	0.004	-0.001	-0.001	-0.003	0.009	0.009	0.009
	(0.89)	(0.34)	(0.63)	(0.31)	(0.11)	(0.05)	(0.28)	(0.76)	(0.76)	(0.76)
Overconfidence		-0.413	-0.056	-0.240	0.576	0.552	0.691	-0.233	-0.447	0.001
		(1.07)	(0.22)	(0.57)	(2.86)***	(2.61)**	(3.05)***	(0.50)	(0.72)	(0.00)
Constant	-2.176	-0.990	-2.122	-1.174	-2.286	-2.221	-2.270	-2.074	-2.130	-2.208
	(3.39)***	(1.06)	(2.89)***	(1.24)	(3.64)***	(3.52)***	(3.63)***	(3.07)***	(3.18)***	(3.01)***
Observations	133	84	117	84	132	132	132	133	127	117
Adjusted R-squared	0.47	0.44	0.47	0.44	0.50	0.49	0.50	0.46	0.45	0.47

Table 10: **Turnover and Measures of Overconfidence: Cross-Sectional Regressions (Investors in Highest Turnover Quintile Excluded)**

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). Investors in the highest turnover quintile are excluded. The first regression reports the results for the subgroup of investors that has responded to the questionnaire without an overconfidence measure. In each of the nine 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(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)
Overconfidence variable	-	OC1	OC2	OC3	BTA1	BTA2	BTA3	IC1	IC2	IC3
Gender	-0.135	-0.685	-0.212	-0.643	-0.104	-0.081	-0.083	-0.141	-0.104	-0.363
	(0.36)	(1.46)	(0.52)	(1.37)	(0.28)	(0.22)	(0.22)	(0.38)	(0.27)	(0.89)
Age	-0.014	-0.016	-0.016	-0.016	-0.012	-0.009	-0.010	-0.013	-0.015	-0.019
	(1.84)*	(1.67)*	(2.10)**	(1.76)*	(1.61)	(1.20)	(1.37)	(1.77)*	(1.97)*	(2.43)**
Warrant trader	0.548	0.432	0.447	0.430	0.556	0.572	0.564	0.547	0.517	0.442
	(3.70)***	(2.43)**	(2.96)***	(2.43)**	(3.73)***	(3.92)***	(3.83)***	(3.69)***	(3.41)***	(2.99)***
High risk	0.193	0.167	0.092	0.190	0.230	0.259	0.256	0.199	0.254	0.150
	(0.71)	(0.53)	(0.30)	(0.60)	(0.83)	(0.96)	(0.94)	(0.72)	(0.83)	(0.49)
ln(Portfolio value)	-0.101	-0.051	-0.062	-0.047	-0.105	-0.120	-0.113	-0.100	-0.096	-0.056
	(1.87)*	(0.80)	(1.11)	(0.74)	(1.95)*	(2.24)**	(2.10)**	(1.85)*	(1.73)*	(1.01)
Information	0.000	0.002	0.000	0.004	-0.004	-0.010	-0.009	-0.001	-0.001	-0.002
	(0.04)	(0.15)	(0.05)	(0.34)	(0.39)	(0.86)	(0.74)	(0.10)	(0.10)	(0.20)
Overconfidence		0.530	0.225	0.627	0.243	0.528	0.463	-0.299	-0.712	0.560
		(1.51)	(0.97)	(1.62)	(1.23)	(2.55)**	(2.06)**	(0.67)	(1.21)	(1.88)*
Constant	-0.107	-0.336	-0.371	-0.430	-0.164	-0.167	-0.187	0.020	-0.104	0.051
	(0.17)	(0.39)	(0.56)	(0.50)	(0.26)	(0.27)	(0.30)	(0.03)	(0.16)	(0.08)
Observations	131	83	115	83	130	130	130	131	125	115
Adjusted R-squared	0.15	0.10	0.10	0.10	0.16	0.19	0.18	0.15	0.15	0.13

Table 11: **Summary of Findings**

This table summarizes our findings on the correlation coefficients of our nine overconfidence measures and three measures of trading volume and the results of the cross-sectional regression analysis presented in the previous tables. * indicates significance at 10%; ** indicates significance at 5%; *** indicates significance at 1%.

		All respondents to the questionnaire			Highest turnover quintile excluded		
		ln(Number of stock market transactions)	ln(Number of stock market purchases)	ln(Turnover)	ln(Number of stock market transactions)	ln(Number of stock market purchases)	ln(Turnover)
Correlation coefficients	OC1	negative	negative	positive	negative	**negative***	positive
	OC2	negative	negative	positive	negative	negative	positive
	OC3	negative	negative	positive	negative	negative	**positive***
	BTA1	**positive****	**positive***	positive	**positive*****	**positive****	positive
	BTA2	**positive***	**positive***	positive	**positive****	**positive****	**positive*****
	BTA3	**positive****	**positive***	positive	**positive*****	**positive****	**positive****
	IC1	negative	negative	positive	negative	negative	negative
	IC2	negative	positive	negative	negative	positive	negative
	IC3	positive	positive	positive	positive	positive	positive
Cross-sectional regressions	OC1	negative	negative	positive	negative	negative	positive
	OC2	positive	positive	positive	negative	negative	positive
	OC3	negative	negative	positive	negative	negative	positive
	BTA1	**positive****	**positive****	positive	**positive*****	**positive*****	positive
	BTA2	positive	positive	positive	**positive****	**positive****	**positive****
	BTA3	**positive***	**positive****	positive	**positive*****	**positive*****	**positive****
	IC1	positive	positive	positive	negative	negative	negative
	IC2	negative	negative	negative	negative	negative	negative
	IC3	positive	positive	positive	positive	positive	**positive***

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