Financial Overconfidence Over Time — Foresight, Hindsight, and Insight of Investors*

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Abstract

Overconfidence is among the most popular psychological explanations for investing behavior of private households. It has been linked to portfolio turnover, diversification, and risk taking, with mostly negative consequences for investors. In a panel survey of self-directed investors, who own an online brokerage account at a UK bank, we ask for stock market and portfolio expectations and derive several overconfidence measures from the responses. We find that in general overconfidence is present in our sample. We then match the survey data with investors' actual transactions and portfolio holdings, and find an influence of overplacement on trading activity, of overprecision and overestimation on degree of diversification, and of overprecision and overplacement on risk taking. Overconfidence hereby leads to increased trading activity, higher risk taking, and less diversification. We explore the evolution of overconfidence over time and identify a role of past success and hindsight on subsequent degree of overconfidence.

JEL-Classification Codes: G02, G11

Keywords: Overconfidence, Trading, Diversification, Risk Taking, Expectations, Hindsight.

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1 Introduction

Overconfidence is now for more than a decade among the most popular psychological explanations for investing behavior of private households. It has been linked to portfolio turnover (Odean, 1998; Glaser and Weber, 2007), diversification (Goetzmann and Kumar, 2008) and risk taking (Dorn and Huberman, 2005; Nosić and Weber, 2010) of investors. The implications of overconfidence in this context are mostly viewed negatively, leading to excessive trading, underdiversification, and increased risk taking. However, little is known about the development of financial overconfidence over time and its dynamic interaction with trading behavior. We fill this gap by providing for the first time a comprehensive study of financial overconfidence in its different facets, its consequences for various aspects of real investing behavior and its development over time.

In a panel survey of private investors at a large UK bank, we ask participants for their return expectation and risk perceptions regarding the UK stock market and their own portfolios. From these expectations we construct three measures of overconfidence related to the three types of overconfidence commonly identified in the literature: overestimation, overplacement, and overprecision (cp. Moore and Healy, 2008). The survey is administered every three months between September 2008 and September 2010 resulting in a total of nine survey rounds, which cover one of the most interesting times in recent stock market history. Participants are affluent, self-directed investors, who own on online brokerage account at the bank. Their transactions are recorded, which allows us to combine the survey responses with the actual trades and portfolio holdings of participants. The trading and portfolio data include information about trading frequency, turnover, diversification, and risk taking of investors. This enables us to analyze the most prevalent phenomena that have been linked to overconfidence in a dynamic setting.

We extent existing literature in several ways, as before the link between overconfidence and real trading behavior has often been only postulated (Odean, 1998) or verified by proxies (Barber and Odean, 2001; Goetzmann and Kumar, 2008), or the analysis has been limited to one particular form of overconfidence (Graham, Harvey, and Huang, 2009). In rare cases two types of overconfidence are considered Glaser and Weber (2007), but then again the dependent variable is confined to trading volume. Besides our systematic and multi-dimensional treatment of overconfidence and investing behavior, we aim for a better understanding of dynamic development of overconfidence as suggested by Gervais and Odean (2001).

We first document the presence of overconfidence in its various facets in our panel. Participants overestimate their actual portfolio returns on average by a large degree and also expect portfolio Sharpe ratios to be higher than ex post realized values. They further believe that their portfolios will outperform the market, while at the same time they perceive own portfolios as less risky on average. This finding of overplacement is supported by survey responses in which participants describe themselves to be better informed, more experienced and more skillful in investing. Overprecision is also widespread in the investor population. Depending on whether confidence intervals are compared to historical volatilities or option implicit volatilities, elicited confidence intervals are too narrow by a factor two to four. Miscalibration for own portfolios tends to be worse than for the market in general. With all overconfidence measures we observe great cross-sectional heterogeneity, which is the prerequisite to explain differential behavior in trading and risk-taking. However, for most measures a majority of participants exhibit overconfidence.

As our main result we establish a relationship between overplacement and trading activity, between overestimation, overprecision, and degree of diversification, and between overplacement, overprecision, and risk-taking. We do not find overprecision to be relevant for trading activity, which is in contrast to the theoretic literature on overconfidence in finance (Odean, 1998; Daniel, Hirshleifer, and Subrahmanyam, 1998), but in line with previous empirical results (Glaser and Weber, 2007; Graham et al., 2009). All findings are established in dynamic panel regressions, suggesting a dynamic relationship between overconfidence and trading behavior which goes beyond the view of overconfidence as a stable personality trait. The findings suggest a nuanced role of financial overconfidence for all examined aspects of investing behavior, and they round off and clarify the previous view on this complex relationship.

To learn more about the dynamics of overconfidence we examine persistence and possible causes of overconfidence. We find rank-correlations of overconfidence measures over time mostly between 0.1 and 0.4, suggesting some cross-sectional stability in the degree of overconfidence, but also considerable variability over time (cp. also Glaser, Langer, and Weber, 2009). It has been proposed that this variability might be driven by past success and failure, with success leading to an increase in overconfidence through a self-attribution bias (Gervais and Odean, 2001; Daniel et al., 1998). Hereby success can be actual investment success or estimation success with regard to the elicited expectations. It is even possible that perceived success not backed by reality affects overconfidence (cp. Barberis and Thaler, 2003).

We find a strong influence of past investment success on overestimation for the subsequent estimation period, but no effect on overplacement. This means that after good portfolio returns investors overestimate their returns in the future, but after having outperformed the market, they do not necessarily expect to outperform the market again. Analyzing the role of potentially erroneous beliefs about past performance, we observe a positive correlation between perceived and actual portfolio returns, showing that investors have some idea about their realized performance, but still the estimation error is large. Although investors do not consistently overrate their past performance, perceived past success nevertheless contributes to increased levels of overconfidence in foresight. We show that investors, who hold inflated views about past portfolio returns are subsequently subject to higher levels of overplacement and overestimation.

The remainder of the paper is organized as follows: in section 2 we review the overconfidence literature in finance and develop hypotheses for the empirical analysis. Section 3 presents the data set, which consists of investors' survey responses and matched trading and portfolio data. In section 4 we define measures of overconfidence and report descriptive statistics. Section 5 contains our main results with regard to investing behavior, section 6 reports findings about the dynamics of overconfidence, a final section concludes.

2 Literature and Hypotheses

Overconfidence is a well-documented bias in the psychology of judgment and has readily found its way into finance literature. While the notion of overconfident investors seems to have some immediate appeal in describing the behavior of financial market participants, recent evidence suggests that the underlying mechanisms are more complex. First of all the term overconfidence encompasses at least three distinct phenomena to which we will refer to as "types of overconfidence". In analyzing these different types, we adopt the terminology of Moore and Healy (2008), who distinguish between overestimation, overplacement, and overprecision.[1]

People can be overconfident with regard to their absolute ability or performance in a domain; they overestimate their personal outcome, for example the grade they will achieve in an exam or the time they will need to run a Marathon (Grieco and Hogarth, 2009). Overestimation is often demonstrated in performance judgments after experimental tasks, and it has been shown that levels of overestimation increase with difficulty and personal importance of the tasks (Moore and Healy, 2008; Frank, 1935). Investing ranks high on both dimensions, therefore we expect considerable overestimation in judgments of financial performance. The counterpart to overestimation in relative comparisons is overplacement, also known as the better-than-average effect (for a review cp. Alicke and Govorun, 2005). It describes the tendency of people to view themselves above average in many domains, for example almost 90% of a sample of US drivers claim to be above average with regard to driving safety Svenson (1981). Overplacement is present in judgments of skills and abilities

[1] Often also overoptimism (Weinstein, 1980) and illusion of control (Langer, 1975) are associated with overconfidence in a broad interpretation of the term.

Kruger and Dunning (1999) as well as personality traits (Alicke, Klotz, Breitenbecher, Yurak, and Vredenburg, 1995). In contrast to overestimation, levels of overplacement are highest for easy tasks (Kruger, 1999; Moore and Cain, 2007).

Finally, overprecision occurs in questions for ranges in which an unknown value will fall with a certain probability. Usually people submit far to narrow intervals (Alpert and Raiffa, 1982; Klayman and Soll, 2004), regardless whether general knowledge questions (e.g. "length of the Nile", cp. Russo and Schoemaker, 1992) or financial values (e.g. "value of the Dow in one year", cp. Glaser et al., 2009) are target of the estimation. Often less than 50% of the true values fall within 90% confidence intervals, indicating severe miscalibration. While it has been argued that the three presented types of overconfidence share a common psychological basis (Larrick, Burson, and Soll, 2007), correlations are often found to be low or even negative (Glaser et al., 2009; Moore and Healy, 2008). We will thus document the different types of overconfidence separately and state as our first hypotheses that investors are overconfident.

H1: Private investors are overconfident with regard to their financial market expectations. Overconfidence materializes in the form of overestimation, overplacement, and overprecision.

H1a: Different types of overconfidence are unrelated.

Overconfidence has been introduced to finance to explain long-standing anomalies in investor behavior such as underdiversification (Blume and Friend, 1975) and excessive trading (Odean, 1999; Barber and Odean, 2000). The underlying reasoning is that overconfident investors believe in their investing skills and their private information, and therefore they engage in frequent trades, concentrate on few favorable assets, and take on additional risk. In financial models, overprecision has been linked to increased trading volume and overreaction in stock markets (Odean, 1998; Daniel et al., 1998). This theoretic link is used by Odean (1999) and Barber and Odean (2000) to motivate their findings of high individual trading activity, but the relationship is established solely on argumentative grounds. Barber and Odean (2001) introduce gender as a proxy for overconfidence and find that men trade more frequently than women. However, gender might as well proxy for risk-aversion or other properties.

More recent studies directly relate empirical measures of overconfidence from surveys to trading behavior of investors. Glaser and Weber (2007) find a positive effect of overplacement on individual trading volume, but contrary to theory they do not observe an influence of overprecision. Graham et al. (2009) confirm the role of overplacement using a measure based on return expectation. They further demonstrate a strong effect of investors' perceived competence which might be related to overconfidence. Dorn and Huberman (2005) also report a positive impact of overplacement on turnover, while they find no effect of measures for biased self-attribution and illusion of control. Finally, Grinblatt and Keloharju (2009) show a positive influence of overconfidence (self-confidence corrected for competence) on trading activity.

Neither of the three overconfidence measures in Dorn and Huberman (2005) is related to portfolio diversification, and results for risk-taking are mixed, depending on whether fraction of risky investments or portfolio volatility is analyzed. Goetzmann and Kumar (2008) employ a different strategy to identify an effect of overconfidence on diversification; they use turnover as a proxy for overconfidence and find a negative effect of turnover on diversification. This result relies on a robust relationship between overconfidence and turnover and leaves open which type of overconfidence drives the effect. Nosić and Weber (2010) experimentally test for a relationship between overconfidence and risk-taking and show an increase in risk-taking with higher overprecision. Financial literature in general supports the view that there is a fairly established effect of overconfidence (namely overplacement) on trading volume, while its role for diversification and risk-taking is less well understood. Our contribution is in systematically analyzing the effect of all types of overconfidence on trading, diversification and risk-taking.

H2: Overconfident investors trade more frequently, hold underdiversified portfolios and take more financial risk.

The panel structure of our data allows us to explore the evolution of overconfidence among investors over time. The models of Gervais and Odean (2001) and Daniel et al. (1998) suggest that overconfidence will change dynamically with success and failure. Outcomes that confirm a persons' beliefs and actions tend to elevate confidence too much, while contradicting outcomes weaken confidence too little. This biased self-attribution leads to greater overconfidence after successes and reduced overconfidence after failure. Or, as Gervais and Odean (2001) put it, investors "learn to be overconfident". Deaves, Lüders, and Schröder (2010) provide some evidence for financial professionals that indeed success in estimating returns of a stock market index leads to higher overprecision in the subsequent period. The alternative hypothesis that feedback helps people to become less overconfident or better calibrated has found little support even in controlled experiments under ideal feedback conditions (cp. Pulford and Coleman, 1997, and the literature therein).

H3: Overconfidence depends on previous outcomes. Success (estimation success or investment success) leads to increased overconfidence.

While financial market outcomes can be measured objectively, it is possible that subjectively perceived success is more important for the genesis of overconfidence. In particular, when actual and perceived values fall apart and investors view the past rosier than justified. Hindsight effects have been assumed to contribute to overconfidence (Hoch and Loewenstein, 1989; Hawkins and Hastie, 1990). In their survey on behavioral finance Barberis and Thaler (2003, p.1064) write: "Overconfidence may in part stem from two other biases, self-attribution bias and hindsight bias. [...] If people think they predicted the past better than they actually did, they may also believe that they can predict the future better than they actually can." Winman, Juslin, and Björkman (1998) show a systematic relation between hindsight bias and overconfidence in foresight, which they describe as the confidence-hindsight mirror effect. In contrast, Biais and Weber (2009) do not find a relationship between hindsight and overconfidence in a financial context. We adopt a broader notion of hindsight here, which does not only include the classical hindsight bias (overestimation of the probability of having predicted the correct outcome), but also other hindsight effects such as overestimation of past investment success. We expect hindsight to contribute to overconfidence.

H4: **There exists a positive and systematic relationship between hindsight and overconfidence.**

3 Data

To test for overconfidence and its consequences for investing behavior, we obtain survey responses and transaction data for a sample of clients at Barclays Stockbrokers, a UK direct brokerage provider. Barclays is one of the largest banks in the UK and attracts a wide variety of customers (for demographic characteristics of its clients see Egan, Merkle, and Weber, 2010). The accounts are self-directed in the sense that customers receive no direct investment advice, but they can inform themselves on special web pages provided by the bank; most transactions are processed online.

In cooperation with Barclays Wealth, we conduct a repeated survey, which takes place every three months, starts in September 2008 and ends in September 2010. For the initial survey a sample of the banks client base is invited via e-mail to participate in the online questionnaire (for details on the stratified sampling procedure see Weber, E.U.Weber, and Nosić, 2010). In total 617 clients of the bank participate in the survey, 394 of which participate multiple times. 189 participants complete at least five rounds, and 52 answer the questionnaire in all rounds. We have a minimum of 130 observations for each of the nine rounds. In particular, the survey includes questions for expectations of investors, which are our main source for overconfidence assessments. Additionally we elicit several psychological constructs related to overconfidence.

Our data also include the trading records of all investors, who at least once respond to the panel survey. For the time period between June 2008 and December 2010 we observe 49,372 trades with a total trading volume of £258,940,694.[2]. Of these trades about 75% are in stocks, the remaining trades include bonds, derivatives, mutual funds and ETFs. Panel A of table 1 shows descriptive statistics of investors trading activity on a per round basis (3 month). On average 70% of investors trade within each survey period, among those who trade the mean trading frequency is 11.9 (median 5) and mean trading volume is £62,943 (median £9,499). Trading activity is highly skewed with some very frequent and high volume traders. We calculate turnover by dividing trading volume through the sum of the portfolio value at the beginning and the end of each survey period.[3] Average three-month turnover is 39% of portfolio value (median 9.8%), if investors who do not trade are taken into account this values drops to 28% (3.1%). We will later use the variables of Panel A as our measures for trading activity.

Combining trading data with a snapshot of investors' portfolios we are able to calculate portfolio statistics for our survey period. The median portfolio is worth £41,687 (mean £314,663). Panel B of table 1 shows our measures for degree of diversification. A simple indicator is the number of portfolio positions investors hold. Most investors own between 1 and 15 assets, with the average (median) at 15.7 (12), which exceeds typical values in other studies on individual investors (Barber and Odean (2000): average 4.3, Goetzmann and Kumar (2008): average 4.7, Glaser and Weber (2009): average 6.8), but is still less than theoretically necessary to obtain a "well-diversified" portfolio ($>$ 30 stocks, Statman, 1987). We calculate a Herfindahl-Hirschmann-Index (HHI) of portfolio diversification by taking for each investor the sum of squared portfolio weights. We follow the methodology of Dorn and Huberman (2005) in treating mutual funds as if they consisted of 100 equally-weighted positions. The median HHI amounts to 0.14, which corresponds to a portfolio of seven equally

[2]We include three month prior to our first survey round and three month after our last survey round

[3]The convention to use twice the portfolio value (or half of trading volume) has been introduced by Odean (1999). He finds average monthly turnover of 6.5%, while Dorn and Huberman (2005) report 18%. Scaled up to three month our value lies between these results.

weighted securities. The above reported number of portfolio positions thus overstates the degree of diversification among investors. As a further measure of portfolio diversification, we consider normalized variance as defined by Goetzmann and Kumar (2008). Normalized variance is the ratio of portfolio return variance and average return variance of assets in the portfolio. The mean value of 0.55 suggests that portfolio diversification reduces variance by about one half; again there is great cross-sectional heterogeneity.

Panel C of table 1 displays measures of portfolio risk we use to analyze financial risk taking of investors. We calculate portfolio return volatility over a one-year horizon. The mean of 0.37 is well above average UK stock market volatility during the same period of time (0.26). This is reflected also in relative volatility, which we define as portfolio volatility divided by market volatility. But higher risk taking is not explained by higher exposure to market risk, as the average portfolio beta is just 0.84. Instead, the above documented lack of diversification is responsible for high risk levels of investors. Dorn and Huberman (2010) argue that portfolio based measures are hard to evaluate for investors, as they orient themselves at individual securities and disregard correlations between securities; they instead propose a value-weighted average of the return volatilities of portfolio components. This average component volatility (ACV) with a mean of 0.47 exceeds portfolio volatility, as already the related measure of normalized variance suggested. Finally, there is also a survey-based measure of risk taking which is the fraction of a hypothetical £100,000 participants would allocate to the stock market as opposed to a risk-free investment. The average is about 54%, but the range is between investing nothing and investing everything (Cp. Weber et al., 2010, for an in-depth analysis of this investment task.).

4 Financial Overconfidence

4.1 Overprecision

We begin our analysis of investor overconfidence with overprecision (or miscalibration), as it is constituent for financial models of overconfidence. In Odean (1998) traders overestimate the precision of a private signal they receive, which then renders their posteriors more precise than those of a well-calibrated trader. They consequently underestimate the volatility of assets. Empirically, confidence intervals are frequently used to elicit a measure for precision (e.g. Glaser and Weber, 2007; Deaves et al., 2010; Glaser et al., 2009). Our survey questions are designed similarly to those studies:

We would like you to make three estimates of the return of the UK stock market (FTSE all-share) by the end of the next three month.

- *Your best estimate should be your best guess.*
- *Your high estimate should very rarely be lower than the actual outcome of the FTSE all-share (about once in 20 occasions)*
- *Your low estimate should very rarely be higher than the actual outcome of the FTSE all-share (about once in 20 occasions)*

Please enter your response as a percentage change.

Participants are asked to submit a best estimate for the return of the UK stock market and, in an additional question, also for their own portfolios. Both estimates are made for a time horizon of three month to avoid overlapping observations. The best estimate is in each case followed by questions for a high and a low estimate, which together yield a 90%-confidence interval. Applying the method of Keefer and Bodily (1983), it is possible to back out implicit expected volatility from these confidence intervals. We prefer this indirect way of elicitation to direct volatility estimates, as it is simpler and more intuitive (cp. Dave, Eckel, Johnson, and Rojas, 2010).

Table 2 shows the width of predicted confidence intervals for stock market returns and portfolio returns. On average participants submitted slightly larger confidence intervals for own portfolios, but the median confidence interval is in both cases 20 percentage points wide. This translates into a volatility of 0.12 on a yearly basis. Given that people hold very different portfolios, it is no surprise that the standard deviation of confidence intervals is larger for portfolio returns. To assess whether these confidence intervals are well calibrated, we use historical volatility of the stock market and of investors' portfolios as a benchmark. For the market additionally option implied volatility is available. Our miscalibration measures are then defined as the difference between benchmark volatility and estimated volatility from confidence intervals.[4] The descriptive statistics in table 2 show that investors exhibit strong overprecision. Their volatility estimates fall short benchmark volatilities by on average 0.14 to 0.23 (median 0.11 to 0.16), meaning that their confidence intervals are too narrow by a factor 2 to 2.5. Miscalibration significantly exceeds the neutral value of zero ($p < 0.001$). Depending on the benchmark between 83% and 89% of all observations are overprecise (> 1) for the stock market and 85% for own portfolios.

The high levels of overprecision are due to the highly volatile markets during our survey period. Our benchmarks reach volatilities between 0.4 and 0.5, which implies that at certain times confidence intervals of up to 80 percentage points would have been appropriate. Figure 1 shows the development of miscalibration over time, and indeed it spikes with the high volatilities in the immediate financial crisis, as investors do not adjust confidence intervals sufficiently. However, there is overprecision for all rounds of the survey. While with different benchmarks the level of miscalibration slightly changes, the rank-order of participants is preserved.

Another way to assess calibration are hit rates, which should be close to 90% for 90% confidence intervals. We calculate hit rates in the cross section of investors (see table 2):

[4]While Glaser et al. (2009) simply use one divided by estimated volatility as a measure for overprecision, but in a panel study a benchmark volatility is crucial, as the same estimated volatility can be appropriate or overprecise depending on the current market enviroment.

Only about half of the time do confidence intervals cover the later realized value. This shows that miscalibration is not only present compared to some abstract benchmark, but also leads to investors frequently missing the real outcome by their estimates.[5] It has been argued that experts give more precise (and thus more informative) estimates, while hit rates remain constant (McKenzie, Liersch, and Yaniv, 2008). If this was the case, our miscalibration measure would punish these more knowledgeable investors. However, the correlation between miscalibration and hit rate is significantly negative (-0.37), suggesting that narrower confidence intervals are not more informative. In general, our results support H1 with regard to overprecision.

4.2 Overplacement

Measures for overplacement (or the better-than-average effect) involve a comparison to other investors. We ask survey participants for their agreement to the following statements:

1. I believe my investing skill is above average.

2.Compared to an average person, I am informed about current financial conditions.

3.Compared to an average person, I am informed about investing in general.

4. I have more experience with investing than the average person.

Responses are given on a seven-point Likert scale ranging from "strongly disagree" to "strongly agree". The question format of the first question is similar to a better-than-average question in Glaser and Weber (2007), while questions two and three are related to a better-than-average measure in Dorn and Huberman (2005) and Dorn and Sengmueller (2009). We add investing experience as it covers another facet of investing ability and knowledge. We admit that the comparison to the average person instead to other investors might inflate levels of overplacement, but this should be inconsequential for the cross-sectional distribution of overplacement, which is our main interest for the later analysis. Panel A of

[5] In a strict sense the 90%-criterion applies only on an intra-participant basis, for which we have too few observations. We nevertheless calculate the personal hit rate for those who participated at least five times. The average individual hit rate is 0.48 and thus close to the overall hit rate.

table 3 shows how investors rate themselves with regard to the statements. Participants believe that their investing skill is slightly above average with a mean of 4.4. Higher levels of overplacement are observed for being informed and being experienced (5.4 and 5.6). All three values are significantly above the neutral value of 4 ($p < 0.001$). While a moderate fraction of 45% thinks to possess above average skills, a large majority agrees to be better informed and more experienced than others. Correlations between the three evaluations are relatively high (0.5-0.7), Cronbach's alpha amounts to 0.75. We therefore combine the statements in a single overplacement measure by taking the average of the three ratings.

Due to time considerations, these statements were included only in the entry questionnaire of the survey and were not repeated in each survey round. If investors hold stable views of their skills and abilities (as argued for example by Larrick et al., 2007), we can still use them in our panel analysis. However, to generate time-varying measures of overplacement we will apply an alternative strategy. Graham et al. (2009) propose the difference between forecasts of own portfolio return and forecasts of the stock market return as a proxy for the better-than-average effect. The interpretation is straightforward: Market returns define the average an investor can expect to earn and any expected outperformance means to be better than this average. The above stated questions for best estimates of portfolio and stock market return allow us to calculate this expected outperformance. One may object that this measure does not take portfolio risk into account, and investors who take more financial risk are correct in expecting higher returns. To accommodate for this possibility we consider expected volatility of investors, both for their portfolio and the stock market. We construct an expected Sharpe ratio for portfolios and the stock market.[6] The difference between expected portfolio Sharpe ratio and expected market Sharpe ratio proxies for overplacement.

Panel B of table 3 displays descriptive statistic for these variables. On average investors expect to outperform the market by 2.9 percentage points ($p < 0.001$); given the time

[6]We use the 3m-LIBOR as riskfree rate and set negative Sharpe ratios to zero, as these are not well defined.

horizon of three month this amount appears large. About 48% of the time investors expect that their portfolios returns will exceed market returns, in 81% of all cases portfolio returns are expected to at least equal market returns. On a risk-return basis (Sharpe ratio) 49% of investors expect to beat the market, which is a large proportion given that in turn only 24% believe to be beaten by the market. The overplacement in portfolio expectations is perhaps best illustrated in figure 2: consistently over all survey rounds average portfolio return expectations are above average market return expectations (solid lines) and vice versa for risk expectations (dashed lines). Investors thus believe to achieve higher returns while taking less risk. This outperformance expectation in concert with the findings for skill-related statements confirms the presence of overplacement in our investor sample.

4.3 Overestimation

While in finance there has been the casual observation that investors or managers are too optimistic about their return on investment (Dimson, Marsh, and Staunton, 2004; Heaton, 2002), a formal empirical treatment of overconfidence in the form of overestimation is still missing. The relationship between overestimation and optimism is obvious: those who are most optimistic are most likely to fall short of their expectations, in particular if performance involves a large chance element. Overestimation is defined as the difference between expected performance and actual performance (cp. Moore and Healy, 2008), in our case the difference between expected portfolio return and realized portfolio return. Even though it is possible to define this variable also for market returns, overestimation involves the notion of personal achievement, which is only present in portfolio returns.

On average investors in the panel overestimate their portfolio return by 4.3 percentage points (median 1.7, see table 3). While these figures are large and significant ($p < 0.001$), the proportion of overconfident investors is with 55% not overwhelmingly high. There is great heterogeneity with strong overestimation and strong underestimation both present in the data. Given the partly random nature of realized returns, one might suspect that effects in the time series drive this heterogeneity. For instance in the first round of the survey investors predict returns for Sep–Dec 2008, which turn out to be catastrophic due to the progress of the financial crisis. Indeed in this round overestimation reaches highs with an average of 17.9%-points and a proportion of 88% overconfident investors. However, within rounds the standard deviation is only slightly smaller than for the whole panel, indicating that also differences between individuals are considerable. We are thus confident that our measure of overestimation might contribute to explain investing behavior. We confirm H1 with respect to the presence of overestimation in the investor population.

As we have now collected evidence about all three types of overconfidence, we examine the relationship between these measures. Deaves, Lüders, and Luo (2009) report positive but low and not significant correlations between different types of overconfidence, while Glaser and Weber (2007) find even a negative correlation between overprecision and overplacement (also not significant). Table 4 shows a correlation matrix for the measures defined in this section. Miscalibration variables are highly correlated among each other (0.71) but show slightly negative correlations to other types of overconfidence. The agreement to better-than-average statements is positive, but lowly correlated to the expectation to outperform or beat the market. It seems that the two describe different aspects of overplacement and are only weakly related. As anticipated, expected outperformance and the expectation to beat the market on a risk-return basis (Sharpe ratio) are highly correlated (0.62). Overestimation is positively correlated to expected outperformance (0.16), as both measures share portfolio return expectations as one ingredient. But altogether we can confirm H1a in the sense that different types of overconfidence are at most very weakly related.

5 Investing Behavior and Overconfidence

We now bring together the two parts of our analysis: the investing behavior as portrayed in section 3 and the overconfidence measures as defined in section 4. Our goal is to systematically study their relationship, whereas previous literature has mostly examined only parts of this picture. Either the attention was limited to one aspect of investing behavior, or an incomplete typology of overconfidence was considered. Our main contribution is to fill this gap in a dynamic panel setting.

5.1 Trading activity

As excessive trading was most prominently related to overconfidence, we begin with trading activity measures as our dependent variables. We use a trade dummy, which equals one if an investor trades in the respective period, the number and volume of trades, and turnover (all variables as defined in table 1). We take the natural logarithm of number of trades, volume of trades, and turnover as these variables are strongly skewed. As explanatory variables, for overprecision we mostly employ miscalibration with respect to market returns (benchmark historical volatility). Due to the high correlation with the other miscalibration measures we abstain from including several of these variables simultaneously into the regression. However, our results are robust to the use of other specifications. For overplacement the previous analysis revealed that the combined better-than-average proxy and expected outperformance are only weakly related. We thus consider both in our regressions, the former as a time-invariant variable, as it was elicited only once. Occasionally we also report results for the expectation to beat the market on a risk-return basis (Sharpe ratio). Finally we include overestimation as defined in table 3.

Besides our overconfidence measures, we account for a set of further controls, in particular self-reported risk tolerance, which was identified by Dorn and Huberman (2005, p.437) as the "single most important determinant of both portfolio diversification and turnover". We measure risk tolerance as agreement to the statement "It is likely I would invest a significant sum in a high risk investment" (on a seven-point scale). Weber et al. (2010) show that responses in this format are consistent to a more complete assessment of risk attitudes. Demographic variables include gender, age, and family status. We further control for income, wealth and financial literacy.

It was noted that on average about 70% of all investors trade within a three-month period. We thus first examine in a probit model the decision to engage actively in trading at all. Column (1) of table 5 shows the results of this regression. Participants who believe to be more skillful investors and to be more informed about financial markets have a higher propensity to become active in trading. In addition, men are more likely to trade, which contributes to earlier results of gender and trading activity (Barber and Odean, 2001; Deaves et al., 2009). The gender effect, while positive in almost all regressions, is at most marginally significant. This can be due to the fact that we explicitly control for factors gender might be a proxy for (such as risk tolerance or overconfidence), but could also be a consequence of the extreme composition of participants which is 93% male.

Column (2) to (5) report results for number of trades and trading volume. Both variables are far from normally distributed even after logarithmic transformation. Therefore we consider a Poisson regression as an alternative to GLS, yet results are similar. We find a strong impact of risk attitude; more risk tolerant investors trade more frequently and trade higher volumes. Among the overconfidence measures, expected outperformance has a positive influence. Investors who expect to beat the market return engage in more trades and also trade higher volumes. Not surprisingly wealthy investors place larger trades, which follows from no effect on number of trades but a significant effect on trading volume. Interestingly, investors with a higher number of dependents also trade more.

Finally, turnover represents the relation between trading volume and portfolio value. Column (6) of table 5 shows that investors who expect to outperform the market churn their portfolio more often. Male and more wealthy investors also exhibit higher turnover.[7] In column (7) we replace expected outperformance by the related measure of beating the

[7] The latter result is in contrast to previous literature (e.g. Dorn and Huberman, 2005); however, the effect turns around if we use portfolio value as a wealth proxy (similar to Glaser and Weber, 2007). Our interpretation thus is that especially investors with large outside wealth churn their portfolios often.

market on a risk-return basis. The effect is still positive and significant, but the Sharpe ratio difference proves to be less powerful in predicting trading activity. This result is confirmed when we introduce the variable in one of the other reported regressions. We conclude that the degree of overplacement is best reflected in the continuous measure provided by expected outperformance. One might argue that it is portfolio expectations driving our findings, as it is one main ingredient of expected outperformance. However, when we include portfolio return expectations as an additional control (column (8)), expected outperformance remains significant, while return expectations have no direct influence on turnover. Thus the difference between portfolio return expectations and market return expectations is crucial, not some general optimism for own portfolio returns.

We find in all regressions that a measure of overplacement (better-than-average measure or expected outperformance) exerts a positive effect on trading activity, while neither overprecision nor overestimation seems to be relevant. Quite intuitively investors who feel more skillful are more likely to trade, but for the degree of trading the more timely measure of expected outperfromance is relevant. By now there emerges a consensus that overplacement is the facet of overconfidence which is most predictive for trading activity (Glaser and Weber, 2007; Graham et al., 2009; Dorn and Huberman, 2005; Deaves et al., 2009, with the latter finding also a role for miscalibration). We confirm hypothesis 2 that overconfidence has a positive effect on trading activity.

For robustness we consider several alternative specifications. Given that we disentangle the decision to trade at all and trading volume, a Heckman selection approach might help to understand this two-step process. However, the inverse Mills ratio of the participation regression remains insignificant in the second stage suggesting that selection is not severe. We also test a fixed effects model and find coefficients for risk attitude and overconfidence much reduced and mostly not significant. This is not surprising as these variables are at least in part stable individual characteristics. Still the diminished coefficients provide some evidence that part of the effect comes from the time series. We also estimate a static model with the average of turnover through our survey period as dependent variable. Again risk attitude and overplacement are the most important determinants of trading activity.

5.2 Diversification

With number of portfolio positions, a Herfindahl-Hirschman-Index of portfolio weights, and normalized variance, we introduced three indicators of portfolio diversification. For the regression analysis we take the natural logarithm of positions and HHI as these variables are skewed. As the measures represent different aspects of diversification we try to distill a common component by performing a principal component analysis (PCA). The first principal component of this PCA captures about two thirds of the variance and is highly correlated to the other diversification measures. We thus consider it as an additional diversification proxy. To facilitate the interpretation of our results, it is worth noting that diversification decreases with higher values of HHI and normalized variance, while it increases with number of portfolio positions and the PCA-measure.

The set of independent variables remains the same as in our analysis of trading activity. One exception is that we complement miscalibration with respect to market return by miscalibration of portfolio returns, as diversification is a matter of how the own portfolio is perceived. Columns (1),(3),(5) and (7) of table 6 show our baseline regression for the various dependent variables. Risk tolerant investors tend to hold more positions, and are also better diversified with respect to the other measures (although not significantly so for HHI). This result stands in contrast to the finding of Dorn and Huberman (2005) that risk averse investors hold better diversified portfolios. An explanation could be that in a panel setting rounds of high trading activity often coincide with a more diverse inventory of assets, a connection that is much weaker for a larger time span. Indeed, when we run a static regression on average portfolio positions, the effect turns around.

We observe a strong effect of overprecision in portfolio return expectations on all diversification variables. Overprecision reduces the number of portfolio positions, increases HHI and normalized variance, and decreases the PCA-proxy of diversification. The intuition behind this effect is that investors who hold overly precise beliefs about future portfolio returns are unaware of the benefits of diversification, which mainly consist of reducing non-systematic portfolio risk and hereby narrowing the distribution of potential outcomes. However, it is the very nature of overprecision that investors underestimate the width of this distribution and are thus likely to underdiversify. Deaves et al. (2009) argue that calibration measures must be highly specific to explain investing behavior. Indeed, when we replace miscalibration of portfolio returns by miscalibration of market returns, the results differ considerably (see columns (2),(4),(6) and (8)). First of all the, explanatory power of the regressions goes down as becomes evident in R^2, but also the coefficients for miscalibration turn partly insignificant and sometimes change direction. It is obvious that underestimating stock market volatility might not have as direct consequences for portfolio diversification as underestimating portfolio volatility.

As a second overconfidence variable, overestimation contributes to portfolio underdiversification. The sign of coefficients is consistent for all diversification measures, implying that investors tend to hold fewer positions, less diverse portfolio weights (HHI), and higher normalized variance; the effect is significant for HHI, normalized variance, and diversification from PCA. With this finding the picture becomes more complete; investors who believe to be able to identify few very profitable stocks will also neglect diversification. Hypothesis 2 thus holds for diversification, with overprecision and overestimation to increase underdiversification.

Among the demographic variables we identify two effects: Older investors tend to hold better diversified portfolios, as do wealthier investors. For wealth the relation is particularly strong for number of portfolio positions, which is not surprising as wealthy investors hold larger portfolios. The weaker result for other diversification measures leaves open, whether the mechanical accumulation of assets or a genuine understanding of diversification drives this influence. With age it remains unclear, whether older investors become indeed wiser or if they just through the course of their lives have collected a larger number of portfolio holdings. Similar age and wealth effects on diversification are observed by Goetzmann and Kumar (2008) and Dorn and Huberman (2005).

Column (9) of table 6 displays a fixed effects regression of diversification on risk attitude and overconfidence (all time-invariant variables are dropped). It confirms the finding that miscalibration and overestimation decrease diversification, even under the restriction that the individual fixed effect will pick up stable personality characteristics. While the effect size is reduced, fluctuations of overconfidence over time seem to be important for the degree of diversification. For robustness we again perform static regressions with the average of diversification over the survey period as dependent variable. As mentioned above, the somewhat counterintuitive effect of risk attitude disappears in these regressions. Our conclusions with regard to overprecision and overestimation and their impact on diversification however remain valid in a static framework. A caveat to our findings is that investors with higher portfolio volatilities have a harder time to be well calibrated, and of course those who are less diversified tend to own more volatile portfolios.

5.3 Risk taking

Compared to other aspects of investing behavior, the relationship between overconfidence and risk taking has found less attention in finance literature. Using the same dataset, Merkle and Weber (2011) and Weber et al. (2010) identified determinants of risk taking behavior. They find a strong influence of return and risk expectations on portfolio risk and hypothetical risk taking. As our overconfidence variables are mainly based on expectations, we need to carefully control for these effects. Dependent variables are portfolio volatility, relative volatility, average component volatility (ACV), portfolio beta, and fraction of risky investment in the hypothetical risk taking task. We take the natural logarithm of volatility and ACV, as they are skewed.

The analysis of portfolio risk is marred by a potential reverse causality problem, as investors who take higher risk will as a consequence expect higher portfolio returns and higher portfolio risk. Therefore using portfolio expectations to explain risk taking can easily lead to wrong conclusions. We instead include market expectations into the regressions, which should be independent of own portfolio holdings (cp. Merkle and Weber, 2011). A similar strategy can be applied to overprecision, instead of portfolio return miscalibration we rely on market return miscalibration as explanatory variable. Expected outperformance as an overplacement measure is based on the difference between portfolio and market expectations. As argued however, investors who take higher portfolio risk reasonably expect higher portfolio returns. But they have no reason to anticipate higher Sharpe ratios as this variable takes portfolio risk into account.

Table 7 displays regression results of risk taking behavior on overconfidence and controls; columns (1)-(4) report our findings for actual investing behavior. Risk taking increases for higher return expectations, but there is little effect of risk attitude and risk expectations (cp. Merkle and Weber, 2011). Among the overconfidence measures we identify some influence of miscalibration and overplacement. In both cases overconfidence contributes to increased risk taking, participants who underestimate the range of possible market returns and those who expect to beat the market on a risk adjusted basis invest more riskily. While the strength of this result appears not to be overwhelming, one has to take into account that we are forced to use weaker overconfidence proxies. The coefficients for demographic variables show that older and wealthier investors take less risk, while male and financially less sophisticated participants invest more riskily.

The hypothetical risk taking task described in section 2 provides an opportunity to analyze determinants of risk taking in a quasi-experimental setting. Advantages are that results in this task are far less noisy than actual investing, and that aforementioned identification problems do not apply. Columns (5) and (6) show that the impact of expectations and risk attitude are much more distinct for the hypothetical decision, which we attribute partly to the absence of noise but also to the fact that the fraction of risky investment is chosen anew in each survey round, while actual portfolios only change gradually over time. Therefore participants adjust their hypothetical decisions much more to current situational circumstances. We observe a positive influence of miscalibration on risk taking: those who underestimate the variety of probable market returns invest more into the stock market. Additionally those, who believe to be more skillful or better informed, invest more. In contrast to real investing, we find no effect for the overplacement measures based on expected outperformance and Sharpe ratio. This is intuitive, as these variables are related to properties of investors own portfolios, but the risk taking task is not. While the positive impact of gender can be observed for the hypothetical task as well, demographics such as age or wealth are less relevant; a reason could be that in the task the amount to invest is the same for all participants, and they start off from a level situation.

As an overall finding from actual and hypothetical risk taking, we note that miscalibration is positively related to risk taking. In an experimental setting, Nosić and Weber (2010) come to the same conclusion. But unlike overtrading and underdiversification, higher risk taking per se is not an investing bias. Given the miscalibration in the assessment of possible outcomes however, it seems that in particular those who invest more riskily are not fully aware of the potential consequences. They then would invest too much given their risk preferences, which is why we conclude that overconfidence might lead to excessive risk taking. Besides miscalibration, some form of overplacement contributes to risk taking, we thus confirm hypothesis 2. The results are robust to several alternative specifications, for example replacing the tobit model for the risk taking task by a linear model. Again a static model relying on averages of risk taking and controls confirms our findings.

6 Dynamics of Overconfidence

6.1 Success and Failure

Given the impact of different types of overconfidence on various aspects of investing behavior, it is important to understand the dynamic development of overconfidence over time. Our hypothesis 3 suggests a role of past outcomes, in particular success, on future overconfidence. We will define success (and failure) differently for overprecision as opposed to overplacement and overestimation. Overprecision is linked to estimation success as people have to predict confidence intervals for future market and portfolio returns and may adjust intervals in response to outcomes conflicting or justifying their prediction. In contrast, overplacement and overestimation are based on evaluations of relative or absolute performance and thus may be bolstered by past investment success.

Estimation success can be easily defined by confidence intervals that cover the realized value. We compare the group of investors with successful estimates to those who missed the true value by their confidence interval. From a Bayesian point of view it is unclear whether there should be an adjustment at all, as for any confidence interval with a probability of less than one, both outcomes will occur with a certain frequency. In our questions for 90%-confidence intervals, a miss definitely is a stronger signal than a hit. Table 8 displays how participants react to realizations that fall inside or outside their confidence intervals. A clear pattern emerges: those who missed the realized value in the previous round enlarge their confidence intervals by about 5%-points, while those who covered the true value narrow their confidence intervals by 3%-points. These changes are large given that the median confidence interval is about 20%-points wide. The proportion of people who increase their confidence interval is also much larger for those who missed the realized value; all differences are significant at 1%-level. These changes in confidence intervals have direct consequences for miscalibration, investors who previously estimated the range of returns successfully become more overprecise in the subsequent round.

We test this conjecture in a multivariate framework proposed by Deaves et al. (2010). They regress changes in confidence intervals on a dummy variable that indicates whether an investor was previously correct or not and control for changes in market return and market volatility. We expect the coefficient for the dummy variable to be negative, as the univariate statistics suggested that investors decrease confidence intervals after correct estimates. Column (1) of table 9 with the dummy as the sole independent variable yields the same result. Interestingly the coefficients (constant and dummy coefficient) are close to the values observed by Deaves et al. (2010).[8] Suggested control variables (column 2) do not change the negative relationship between correct estimates and subsequent confidence intervals, we further observe that after positive past returns investors tend to decrease intervals. It seems that the results so far unambiguously support hypothesis 3. However, given that investors might not fully recall their previous estimates, might not be aware of the realized value, and thus may only have a very vague idea of estimation success or failure, the findings are surprisingly clear-cut. A caveat to this interpretation is that width of confidence intervals and estimation success are not independent. Investors with confidence intervals that cover the realized value have on average submitted wider intervals. A regression toward the mean would predict narrower intervals subsequently. To control for this effect we add lagged width of confidence intervals to the regression (column 3). Lagged width has a strong negative impact on change of confidence intervals, but more importantly the influence of the estimation success dummy turns around. This raises some doubts about the above findings and the results of Deaves et al. (2010), as a regression toward the mean effect provides an alternative explanation.

Compared to estimation success in a survey task, actual investment success should be much more salient to participants. We again divide participants into two groups, those who experienced portfolio returns that exceeded market returns in the past three month (survey period) and those with portfolio returns lower than market returns. According to the

[8]We choose a pooled regression here to most closely match the approach of Deaves et al. (2010). However, a panel fixed effects regression produces very similar results.

learning-to-be-overconfident hypothesis those who outperformed the market are expected to become more overconfident (Gervais and Odean, 2001). Table 10 shows levels and changes of portfolio expectations and overconfidence measures for the two groups of investors. Successful investors expect higher portfolio returns in the future (7% vs. 6%), and they increase their return expectations compared to the previous round more strongly. This gives rise to more pronounced overplacement: levels and changes of expected outperformance and Sharpe ratio difference are always higher for previously successful investors. However, differences are in general not large and only marginally significant, for instance successful investors expect to outperform the market by 3.1% and unsuccessful investors by 2.7%. While we observe higher levels of overestimation among the previously unsuccessful, overestimation does indeed decrease more strongly for this group.

We draw on the model introduced before and regress changes in overplacement and overestimation on investment success and controls. For investment success we use either a dummy variable that indicates whether an investor outperformed the market in the past three months, or a continuous version, which is the difference between past portfolio returns and market returns. Table 11 reports the results of these regressions. Columns (1)-(4) show that we do not identify an effect of investment success on subsequent overplacement, the explanatory variables even fail to attain joint significance by an F-test. A different picture emerges for changes in overestimation (columns 5–6), investment success encourages participants to overestimate future portfolio returns more strongly; past market returns contribute to this tendency. As past levels of overestimation are not independent of past investment success (as with lower portfolio returns it is more likely to have overestimated returns), a similar concern applies as to changes in confidence intervals. However, when we introduced lagged levels of overestimation in the regression (column 7), the influence of investment success remains robust. A regression toward the mean effect might thus partake in the explanation, but not invalidate the role of previous investment success. Altogether we can only partly confirm hypothesis 3, investment success leads to increased overestimation but not to increased overplacement, and estimation success leads to higher overprecision, which may however be a result of a regression toward the mean effect.

6.2 Hindsight

One reason for the mixed relevance of previous outcomes for subsequent overconfidence might be that investors are not fully aware of the values of these outcomes. The survey does not provide them with information on past returns, and investors beliefs in retrospect might differ from the returns we calculate. Therefore a survey questions asks investors explicitly for past market and portfolio returns. We can thus compare investors' hindsight on returns and the actual values, figure 3 plots post-estimates against realized portfolio returns. The relationship is positive, we find a Pearson-correlation of 0.50 for portfolio returns and of even 0.68 for market returns. This is contrary to Glaser and Weber (2007b), who report no correlation between hindsight portfolio return estimates and realized values. A possible explanation is that during our survey period attention to portfolio returns is amplified due to the financial crisis. Moreover, Glaser and Weber (2007b) use a time period of three years, which renders estimation harder.

But figure 3 also shows large deviations from the 45-degree line, suggesting severe estimation errors. We calculate the difference between estimates and realized values, which indicates whether investors systematically over- or underestimate their own past performance, and the absolute value of this difference, which signifies the magnitude of estimation error. Panel A of table 12 shows that investors overestimate past market returns by on average 2.4%-points ($p < 0.01$), but show no systematic bias for own past portfolio performance. Median estimation errors are large, 5.3%-points for market returns and even 8.5%-points for portfolio returns. However, one has to take into account that in the volatile market environment at the time of our survey pronounced changes in returns occur within days, which exacerbates errors if investors recall a time window only slightly departing from the three months used for calculation of realized returns.[9]

For a relative assessment of past performance we pose the following question to investors in each round of the survey:

Compared to the other investors, how well do you think your portfolio held with us performed in the past three months?

Responses are given on a seven-point scale ranging from "much worse" to "much better". Panel B of table 12 displays results for this evaluation of relative performance, which are on average slightly below the middle point of the scale suggesting that investors believe, their returns were somewhat worse than the returns of other participants. When we now sort investors' realized returns into seven quantiles (corresponding to the seven-point scale) and then subtract this realization from the relative performance evaluation, we obtain a measure for overplacement in hindsight, which indicates whether investors think that they performed better than they really did (in relative terms). On average there is slight underplacement, which directly follows from the low relative performance estimates. An explanation for this underplacement might be poor portfolio returns during the financial crisis. Of course other investors struggle with bad outcomes as well, but it has been shown that egocentrism is present in relative evaluations (Kruger, 1999). This means that individuals rely too heavily on their own performance neglecting the performance of others. To test this conjecture, we regress evaluations of past relative performance on the estimates for past portfolio return and past market return (results not reported). Indeed, relative performance is positively related to own performance and negatively to market performance, but the effect of own performance is about three times as large as the effect of market returns. Thus poor portfolio returns in conjunction with egocentrism may explain underplacement. We can construct

[9] A source of estimation error participants are not responsible for are potential errors in calculation of realized returns. We use price data from Thomson Reuters Datastream which covers more than 90% of portfolio holdings and fill in last observed transaction price for securities without available price data. This should guarantee fairly accurate portfolio return calculations.

a related overplacement measure also from the numeric estimates of past performance discussed above. The difference between estimates for past portfolio return and past market return represents investors' perceived outperformance. On average there is a belief of having underperformed the market by about 1%-point ($p < 0.01$). If survey participants are consistent, the degree of this perceived past outperformance should be closely related to judgments of past relative performance; we find a positive correlation of 0.40.

We have now gathered several measures of investors' perceptions of past performance as opposed to actual performance data used in the previous section. Hypothesis 4 claims that these perceptions in hindsight will induce overconfidence in foresight. We thus split investors into those who overestimate their past portfolio returns and those who do not, and compare the levels and changes in overconfidence variables for the two groups (see table 13). We find that investors who overestimate their past performance not only exhibit higher levels of overconfidence, but also increase these levels more strongly (except for overestimation). We consider an alternative partition based on outperformance in hindsight; again those who believe in having outperformed the market in the past are increasingly overconfident in the future. While in this case the differences mostly do not attain significance, the always positive sign still suggests some robustness of the effect. Differences get even larger if we consider only those investors who believe in having outperformed the market but in reality did not. These investors suffer under a form of hindsight bias that makes them particularly prone to become overconfident. Interestingly, the qualitative evaluations of past relative performance and overplacement do not produce the same pattern of persistently larger levels and changes in overconfidence.

In a multivariate setting we introduce overestimation and outperformance in hindsight as additional explanatory variables for changes in overconfidence. Table 14 shows results, which build on the regression used to test for the influence of actual investment success before. We find a strong impact of perceived past performance on changes in overplacement, and also a marginally significant influence on changes in overestimation. Investors, who believe in having outperformed the market or who overestimate their past investment success, will become increasingly overconfident. We still control for actual success by past outperformance, which is again only relevant for changes in overestimation (results for the success dummy variable are similar). In many situations it might be more important for expectations of investors how successful they think to be than how suscessful they really are. We confirm the relevance of hindsight effects for overconfidence, which supports hypothesis 4. Results are mostly robust to alternative specifications such as a pooled or random effects regression or the addition of lagged overconfidence values.

7 Conclusion

Investors are overconfident in various forms, for example they expect their portfolios to yield higher returns than the market and to be less risky at the same time. They also think to be better informed about financial markets and more skillful in investing than others. Investors are overprecise in their predictions of future returns, when asked for 90% confidence intervals submitted ranges contain the true value less than 50% of the time. And they do not only expect to outperform the market, but frequently overestimate portfolio returns compared to actual outcomes. We document these patterns in investor beliefs and ask the fundamentally important question: Is overconfidence in beliefs relevant for investing behavior?

The response is yes, and while this question has been partly answered in other studies, our approach systematically relates different aspects of investing behavior to all types of overconfidence; figure 4 summarizes our results. Trading activity is spurred by overplacement, the belief to be able to outperform the market. This is intuitive as it appears sensibly to trade only if one expects higher returns than from a buy and hold strategy in the market index. Portfolio diversification in contrast is influence by overprecision and overestimation, investors who are not aware of the range of possible outcomes feel less need to diversify, and those who expect overly high returns from their portfolio as well forgo diversification opportunities. Finally, portfolio risk taking depends on overprecision and overplacement. Investors, who believe to be better than others, take more risk, and those, who underestimate the variance of returns, also take more risk.

The dynamics of overconfidence is driven by actual and perceived success of investors. Estimation success is associated with higher miscalibration for subsequent confidence intervals, and investment success produces higher overestimation of future portfolio returns. However, the effect of realized investment performance is attenuated by the fact that investors are not fully aware of past outcomes. We identify estimation errors for past portfolio and market returns, and that perceived performance can differ a lot from actual performance. As overconfidence is a psychological phenomenon, perceived performance might be at least as important as realized values. Indeed, overestimation and outperformance of investors in hindsight are important determinants of overplacement and overestimation in foresight.

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Table 1: Trading and portfolio statistics

Panel A – Trading activity	n	Mean	Median	Std.Dev.	5th Perc.	95th Perc.
Trade dummy	6020	0.704	1	0.456	0	1
Number of trades	4241	11.92	5	26.31	1	46
Trading volume	4241	62,943	9,499	333,499	201	237,777
Turnover	3903	0.386	0.098	0.684	0.003	2.690
Panel B – Diversification	**n**	**Mean**	**Median**	**Std.Dev.**	**5th Perc.**	**95th Perc.**
Portfolio positions	6406	15.72	12	226.80	2	42
HHI	6384	0.242	0.144	0.253	0.021	0.936
Normalized variance	6264	0.545	0.481	0.260	0.195	1
Panel C – Risk taking	**n**	**Mean**	**Median**	**Std.Dev.**	**5th Perc.**	**95th Perc.**
Portfolio volatility	6472	0.370	0.301	0.306	0.137	0.824
Relative volatility	6472	1.410	1.148	0.851	0.672	2.885
Portfolio beta	6473	0.840	0.810	0.420	0.222	1.541
ACV	6304	0.472	0.418	0.292	0.077	1.016
Risk taking task	2114	0.535	0.500	0.278	0.000	1.000

Notes: The table shows descriptive statistics for measures of trading activity, degree of diversification, and risk taking. The trade dummy equals one if an investor trades within a survey round (=time between to surveys), number of trades is the number of sales and purchases, and trading volume is the value of all purchases and sales. Turnover is trading volume divided by the sum of portfolio value at the beginning and end of survey round (we exclude portfolios <£5,000 and winsorize turnover from above at the 5%-level). Portfolio positions is number of different securities hold in portfolio, HHI is sum of squared portfolio weights, and normalized variance the ratio of portfolio variance and average variance of portfolio components. Portfolio volatility is the volatility of portfolio returns over a one year horizon, relative volatiliy is portfolio volatility devided by market volatility (winsorized at 1%-level from above), portfolio beta is the covariance of portfolio and market returns divided by the variance of market returns, and ACV is the average volatility of portfolio components. Risk taking task is the fraction of money invested in the stock market as opposed to a risk-free asset in a hypothetical investment task.

Table 2: Overprecision

	n	mean	median	Std.Dev.	% overprecise
Width confidence interval market	1957	23.3	20.0	18.6	
Width confidence interval portfolio	2002	24.0	20.0	22.9	
Miscalibration market (hist. vola)	1997	0.142	0.119	0.191	82.7%
Miscalibration market (impl. vola)	1997	0.150	0.151	0.155	89.0%
Miscalibration portfolio	1981	0.228	0.157	0.363	84.9%
Hit rate market	1957	0.45	0.00	0.49	
Hit rate portfolio	2002	0.49	0.00	0.50	

Notes: The table shows the width of confidence intervals (difference between high and low return estimate) in percentage points for UK stock market return and investors' own portfolio return. We exclude investors who violate the condition that high estimate=>low estimate. Miscalibration is historical (or implied) volatility devided by estimated volatility (from confidence intervals). Historical volatility is calculated over a one-year horizon, implied volatility is option implied volatility as represented by the FTSE VIX volatility index. Miscalibration measures are winsorized at a value of 10. Hitrate is a dummy that equals 1 if a confidence interval covered the realized value.

Table 3: Overplacement and overestimation

PANEL A	n	mean	median	Std.Dev.	% > 4
Bta skill	617	4.40	4.00	1.28	45.2%
Bta information	617	5.55	5.50	1.00	88.3%
Bta experience	617	5.38	5.00	1.22	79.9%
Bta combined	617	5.11	5.00	0.98	85.1%
PANEL B	n	mean	median	Std.Dev.	% > 0
Expected outperformance	2106	0.029	0.000	0.086	47.8% (33%=0)
Sharpe ratio difference	1883	0.308	0.000	1.287	48.8% (27%=0)
Overestimation	2081	0.043	0.017	0.193	54.7%

Notes: Panel A shows responses to better-than-average statements (see text) on a 7-point Likert scale (1="strongly disagree" to 7="strongly agree"). Bta combined aggregates the three individual measures. Panel B: Expected outperformance is the difference between estimated portfolio return and estimated market return for the next three month. Sharpe ratio difference is the difference between expected portfolio Sharpe ratio and expected market Sharpe ratio (winsorized at 1%-level). Overestimation is the difference between expected portfolio return and realized portfolio return. Expected outperformance and overestimation are winsorized at 1%-level.

Table 4: Correlations between overconfidence measures

	Misc. mk.	Misc. pf.	Bta	Exp. Outp.	Sharpe	Overest.
Miscalibration market	1					
Miscalibration portfolio	0.71^{***}	1				
Bta combined	-0.14^{***}	-0.16^{***}	1			
Expected outperformance	-0.04^{*}	-0.02	0.12^{***}	1		
Sharpe ratio difference	-0.06^{***}	0.09^{***}	0.07	0.62^{***}	1	
Overestimation	-0.09^{***}	0.00	0.01	0.16^{***}	0.15^{***}	1

Notes: The table shows pairwise Spearman rank correlation coefficients between measures for overprecision (as defined in table 2), overplacement and overestimation (as defined in table 3). Miscalibration market using implied volatilities is not displayed as it is almost identical to miscalibration using historical volatility ($\rho = 0.98$). Correlations are significant at *10%-level, **5%-level, or ***1%-level

Table 5: Trading activity

	trade dummy	ln(# of trades)		ln(trading vol.)		ln(turnover)		
	Probit	GLS	Poisson	GLS	Poisson	GLS		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Risk tolerance	0.016	0.046***	0.028**	0.088***	0.015***	0.009	0.009	0.009
Miscalibration market	-0.450	-0.298	-0.084	-0.859**	-0.019	-0.081	-0.073	-0.070
Bta combined	0.181**	0.048	0.023	0.094	0.008	-0.005	0.001	-0.004
Exp. outperformance	0.083	0.535*	0.521**	1.184**	0.316***	0.357***		0.295***
Sharpe difference							0.012*	
Overestimation	0.208	-0.166	-0.055	-0.202	0.005	0.054	0.096*	0.016
Portfolio return exp.								0.128
Gender	0.525*	0.151	0.031	0.140	-0.012	0.070*	0.056	0.071*
Age	0.004	-0.001	0.000	0.000	0.000	-0.001	-0.001	-0.001
Couple	0.008	-0.007	-0.000	-0.258	-0.040	-0.004	-0.001	-0.001
Dependents	0.048	0.076*	0.035*	0.156**	0.013	0.024	0.025	0.024
Income	-0.024	-0.010	-0.011	0.047	0.004	0.005	0.004	0.005
Wealth	-0.012	-0.001	0.003	0.202***	0.026***	0.020**	0.019**	0.020**
Fin. lit.	0.025	-0.096	-0.037	0.168	0.017	0.015	0.017	0.018
constant	-0.669	1.875***	0.569**	6.632***	1.916***	0.043	0.025	0.022
n	1928	1480	1480	1480	1480	1363	1300	1363
R^2	—	0.036	—	0.125	—	0.093	0.079	0.095

Notes: The table shows panel regressions of trading activity variables on overconfidence measures and controls (including round dummies). Column (1) displayes a panel probit model, column (3) and (5) a panel poisson regression, and the remaining colums a general least squares model with random effects (standard errors are clustered by participant). Columns (2)-(8) are estimated for those who trade only. Dependent variables are a trade dummy (=1 if investor trades), logarithm of the number of trades, logarithm of trading volume and logarithm of turnover. Risk tolerance is measured on a seven-point scale, overconfidence measures are definded in section 4. Demographics: Gender dummy (male=1), age in years, couple dummy (married or co-habiting=1), number of dependents, income, wealth, financial literacy (number of correct answers using four of the basic literacy questions by van Rooij, Lusardi, and Alessie (2011)). Income and wealth are measured in categories (for a full description see Egan et al., 2010), missing values are imputed. Coefficients are significant at *10%-level, **5%-level, or ***1%-level.

Table 6: Diversification

	ln(positions)		ln(HHI)		norm. variance		diversification (PCA)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Risk tolerance	0.016***	0.016***	-0.007	-0.010	-0.006*	-0.006*	0.023**	0.026**	0.028**
Miscalibration portfolio	-0.105**		0.201***		0.134***		-0.391***		-0.217***
Miscalibration market		0.018		-0.284**		0.078*		0.043	
Bta combined	-0.007	-0.014	-0.015	-0.015	0.006	0.005	-0.005	0.001	
Exp. outperformance	-0.020	-0.031	0.223	0.236	-0.068	-0.046	0.037	-0.029	0.191
Overestimation	-0.091	-0.058	0.240***	0.227***	0.067**	0.051*	-0.271**	-0.216*	-0.174**
Gender	0.138	0.125	-0.179	-0.153	0.002	0.009	0.165	0.132	
Age	0.014***	0.013***	-0.013***	-0.012***	-0.002**	-0.002**	0.020***	0.020***	
Couple	-0.085	-0.093	0.178*	0.162	0.039	0.027	-0.213	-0.184	
Dependents	-0.021	-0.016	0.025	0.023	-0.004	-0.005	-0.028	-0.025	
Income	0.002	0.000	-0.065*	-0.067*	0.003	0.004	0.033	0.037	
Wealth	0.080***	0.086***	-0.030	-0.035	-0.005	-0.007	0.078**	0.085***	
Fin. lit.	0.022	0.036	-0.030	-0.056	0.015	0.011	0.002	0.027	
constant	1.131***	1.069***	-0.747**	-0.542	0.573***	0.620***	-1.530***	-1.806***	0.004
n	1941	1907	1939	1904	1934	1883	1934	1883	1934
R^2	0.127	0.109	0.081	0.048	0.122#	0.086#	0.146	0.099	0.068

Notes: The table shows panel regressions of diversification variables on overconfidence measures and controls (including round dummies). Regressions are GLS, column (1)-(4), (7), (8) with random effects and clustered standard errors by participant, column (9) with fixed effects. Columns (5) and (6) are tobit regressions as normalized volatility is bounded at 1 ($^{\#}R^2$ from linear model). Dependent variables are logarithm of the number of portfolio positions, logarithm of a Herfindahl-Hirschmann-index of portfolio weights, normalized variance, and the first principal component of a PCA involving the three other variables. Risk tolerance is measured on a seven-point scale, overconfidence measures are definded in section 4. Demographics: Gender dummy (male=1), age in years, couple dummy (married or co-habiting=1), number of dependents, income, wealth, financial literacy. Coefficients are significant at *10%-level, **5%-level, or ***1%-level.

Table 7: Risk taking

	ln(volatility)	rel. vola	ln(ACV)	beta	risk task	
	(1)	(2)	(3)	(4)	(5)	(6)
Risk tolerance	0.000	-0.001	0.016***	-0.003	0.021***	0.021***
Market return exp.	0.207***	0.369***	0.162***	0.101**	0.315***	0.332***
Market risk exp.	-0.000	-0.003	-0.009*	-0.003	-0.034***	-0.034***
Miscalibration market	0.123***	0.148*	0.072	0.016	0.161***	0.150***
Bta combined	-0.006	0.020	-0.026	0.013	0.036***	0.035***
Sharpe ratio difference	0.011**	0.028***	0.004	0.009*	0.007	
Exp. outperformance						0.088
Overestimation	0.028	0.064	0.010	-0.055	0.039	0.038
Gender	0.106*	0.164*	0.075	0.108*	0.104**	0.109**
Age	-0.006***	-0.009***	-0.003*	-0.002	-0.000	0.000
Couple	-0.026	-0.059	-0.049	-0.032	-0.022	-0.023
Dependents	0.006	0.007	0.017	0.011	0.019**	0.016*
Income	-0.020*	-0.027	-0.022*	-0.007	-0.002	-0.002
Wealth	-0.031***	-0.050***	-0.032***	-0.018**	0.003	0.003
Fin. lit.	-0.056**	-0.125**	-0.053*	-0.053	0.006	0.001
constant	-0.604***	2.432***	-0.333*	1.117***	0.297***	0.306***
n	1815	1817	1793	1817	1835	1930
R^2	0.388	0.129	0.243	0.042	—	—

Notes: The table shows panel regressions of risk taking variables on overconfidence measures and controls (including round dummies). Columns (1)-(4) report GLS-models with random effects (standard errors are clustered by participant), columns (5)-(6) a panel tobit regression. Dependent variables are logarithm of portfolio volatility (1y-horizon), relative volatility, logarithm of average component volatility(ACV), portfolio beta, and fraction of risky investment in the risk taking task. Risk tolerance and market risk expectation are measured on a seven-point scale, market return expectations in %, overconfidence measures are as definded in section 4. Demographics: Gender dummy (male=1), age in years, couple dummy (married or co-habiting=1), number of dependents, income, wealth, financial literacy. Coefficients are significant at *10%-level, **5%-level, or ***1%-level.

Table 8: Estimation success and overprecision

	realization within confidence interval	realization outside confidence interval	difference
Δ CI market return	-0.033	0.047	-0.079***
Proportion of increase	0.341	0.598	-0.256***
Δ CI portfolio return	-0.032	0.056	-0.088***
Proportion of increase	0.347	0.589	-0.242***
Δ Miscalibration market	0.022	-0.017	0.039***
Δ Miscalibration portfolio	0.032	-0.001	0.033**

Notes: The table displays changes of confidence intervals and changes of miscalibration for two groups of investors: those who covered and those who missed the realized value by their confidence interval estimates in the previous round. Miscalibration (benchmark historical volatility) is demeaned by round to eliminate round effects. Proportion of increase shows for both groups the fraction of investors who increased their confidence interval subsequently. Differences between the group are significant at *10%-level, **5%-level, or ***1%-level by a standard t-test and a Wilcoxon rank-sum test.

Table 9: Determinants of changes in confidence intervals

	Change confidence interval		
	(1)	(2)	(3)
Success dummy (correct=1)	-0.079***	-0.069***	0.033*
Past market return		-0.150**	-0.008
Δ Market volatility		-0.019	0.029
Lagged width of CI			-0.633***
constant	0.047***	0.039***	0.151***
n	1041	1041	1041
R^2	0.037	0.044	0.319

Notes: The table shows a pooled regression of changes in estimated confidence intervals for market returns on a success dummy and controls. The success dummy equals one, if the previous confidence interval covered the realized value. Past market return is the return of the FTSE all-share index between the previous and current survey round. Δ market volatility is the change in implied market volatility of the FTSE for the same time period. Lagged width of confidence interval is the estimated width of confidence interval in the previous period. Standard errors are clustered by participant. Coefficients are significant at *10%-level, **5%-level, or ***1%-level.

Table 10: Investment success and overconfidence

	portfolio return > market return	portfolio return < market return	difference
Portfolio return expectations	0.070	0.060	$0.010^{***/**}$
Δ Portfolio return exp.	0.013	0.004	$0.009^{**/-}$
Expected outperformance	0.031	0.027	$0.004^{*/-}$
Δ Expected outperformance	0.005	0.000	0.005
Sharpe ratio difference	0.347	0.256	$0.091^{-/*}$
Δ Sarpe ratio difference	0.086	0.037	0.049
Overestimation	-0.009	0.017	$-0.027^{***/***}$
Δ Overestimation	-0.012	-0.063	$0.051^{-/***}$

Notes: The table displays expectations, overconfidence measures and changes in these variables for two groups of investors: those who outperformed and those who underperformed the market in the previous round. Portfolio return expectations are three-month return estimates for own portfolios, overconfidence variables as defined in table 3. Differences between the group are significant at *10%-level, **5%-level, or ***1%-level by a Wilcoxon rank-sum test / standard t-test.

Table 11: Determinants of changes in overplacement and overestimation

	Δ exp. outperf.		Δ Sharpe diff.		Δ overestimation		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Success dummy	0.007		0.052		0.161***		
Past outperformance		0.026		-0.054		1.024***	0.473***
Past market return	0.017	0.021	0.145	-0.008	0.804***	1.181***	0.667***
Δ Market volatility	0.001	0.001	0.098	0.063	-0.052*	0.034	0.040**
Lagged overestimation							-0.563***
constant	-0.001	0.002	0.038	0.071*	-0.115***	-0.056***	-0.022***
n	1192	1192	959	959	1194	1194	1194
R^2	0.001	0.001	0.000	0.000	0.301	0.503	0.571

Notes: The table shows pooled regressions of changes in overplacement and overestimation on investment success variables and controls. The success dummy equals one, if the previous portfolio returns exceeded market returns. Past outperformance is the difference between past portfolio return and past market return in %-points. Past market return is the return of the FTSE all-share index between the previous and current survey round. Δ market volatility is the change in implied market volatility of the FTSE for the same time period. Lagged overestimation is the level of individual overestimation in the previous period. Standard errors are clustered by participant. Coefficients are significant at *10%-level, **5%-level, or ***1%-level.

Table 12: Estimation of past returns

Panel A	n	Mean	Median	Std.Dev.	5th Perc.	95th Perc.
Overestimation mk (hindsight)	2108	0.024	0.012	0.124	-0.131	0.224
Overestimation pf (hindsight)	2088	0.005	0.001	0.197	-0.298	0.289
Absolute error market	2108	0.077	0.053	0.074	0.004	0.223
Absolute error portfolio	2088	0.128	0.085	0.684	0.008	0.413
Panel B	**n**	**Mean**	**Median**	**Std.Dev.**	**5th Perc.**	**95th Perc.**
Relative performance	2101	3.723	4.000	1.250	2.000	6.000
Overplacement (hindsight)	2074	-0.238	0.000	2.116	-4.000	3.000
Outperformance (hindsight)	2104	-0.009	0.000	0.133	-0.25	0.19

Notes: Panel A displays overestimation in hindsight, the difference between estimates of past return and the realized values for the UK stock market (mk) and own portfolios (pf), both winsorized at 1%-level. Absolute error is the absolute value of this difference. Panel B shows relative past performance judgments of investors, the difference of this judgments and realized perfomance (quantile-sorted), and the numeric difference between estimates for past portfolio return and past market return.

Table 13: Perceived past performance and overconfidence

	Overestimation pf (hindsight)			Outperformance (hindsight)		
	> 0	< 0	difference	> 0	< 0	difference
Portfolio return exp.	0.065	0.065	$0.000^{*/-}$	0.073	0.066	0.007
Δ Portfolio return exp.	0.020	0.002	$0.018^{-/**}$	0.011	0.006	0.005
Expected outperformance	0.030	0.027	0.003	0.035	0.030	0.006
Δ Expected outperf.	0.011	-0.002	$0.013^{**/**}$	0.004	0.000	0.004
Sharpe ratio difference	0.326	0.279	0.046	0.373	0.305	$0.068^{*/-}$
Δ Sharpe ratio diff.	0.256	-0.053	$0.309^{**/***}$	0.098	0.000	0.098
Overestimation	0.066	0.018	0.048	0.056	0.035	0.021
Δ Overestimation	-0.069	-0.006	$-0.064^{***/***}$	-0.010	-0.064	$0.053^{**/***}$

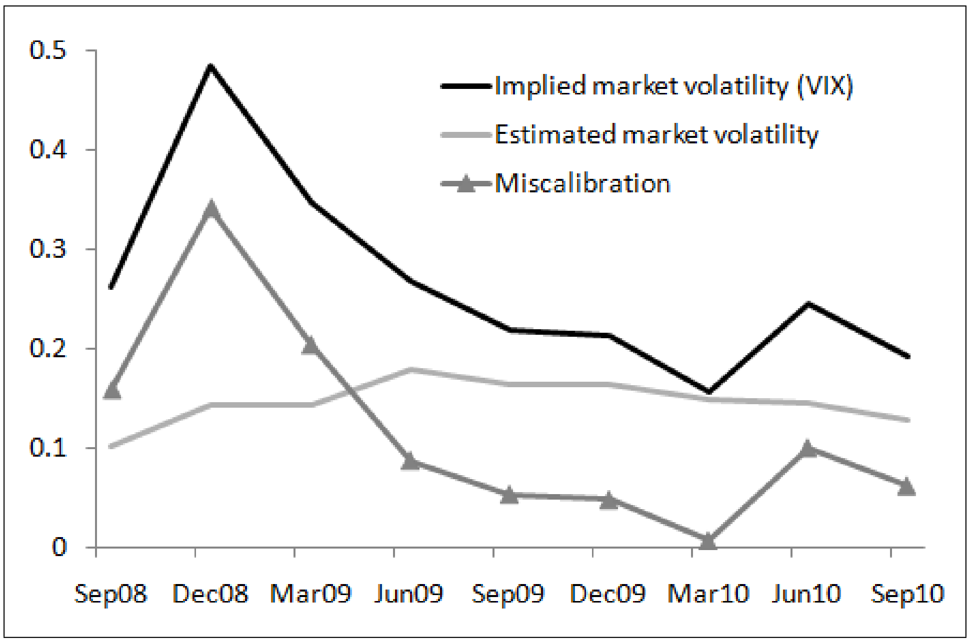
Notes: The table displays expectations, overconfidence measures and changes in these variables for two partitions of investors: those who overestimate vs. those who underestimate past portfolio returns, and those who believe in having outperformed the market vs. those who believe in having underperformed the market. Portfolio return expectations are three-month return estimates for own portfolios, overconfidence variables as defined in table 3. Differences between the group are significant at *10%-level, **5%-level, or ***1%-level by a Wilcoxon rank-sum test / standard t-test.

Table 14: Actual and perceived success as determinants of changes in overconfidence

	Δ exp. outperf.		Δ Sharpe diff.		Δ overestimation	
	(1)	(2)	(3)	(4)	(5)	(6)
Past outperformance	-0.041	0.036	-0.953	0.371	0.957***	1.022***
Past market return	-0.008	-0.023	-0.376	-0.584	1.164***	1.159***
Δ Market volatility	0.004	-0.010	0.072	-0.160	0.023	0.014
Outperformance (hindsight)	0.088***		1.828***		0.100*	
Overestimation (hindsight)		0.091***		1.525***		0.067
constant	0.006*	0.004	0.130*	0.089	-0.054***	-0.057***
n	1188	1189	956	957	1189	1190
R^2	0.001	0.003	0.001	0.007	0.488	0.489

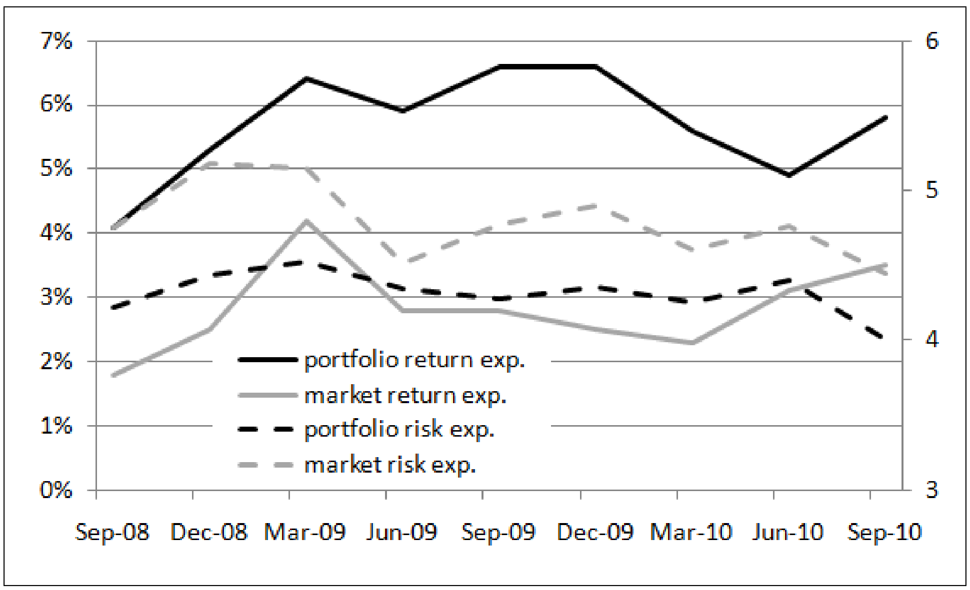
Notes: The table shows fixed effects panel regressions of changes in overplacement and overestimation on actual and perceived investment success and controls. Past outperformance is the difference between past portfolio return and past market return in %-points. Past market return is the return of the FTSE all-share index between the previous and current survey round. Δ market volatility is the change in implied market volatility of the FTSE for the same time period. Outperformance (hindsight) is the difference between estimated past portfolio return and estimated past market return. Overestimation (hindsight) is the difference between estimated past portfolio return and realizedportfolio return. Coefficients are significant at *10%-level, **5%-level, or ***1%-level.

Figure 1: Miscalibration over time



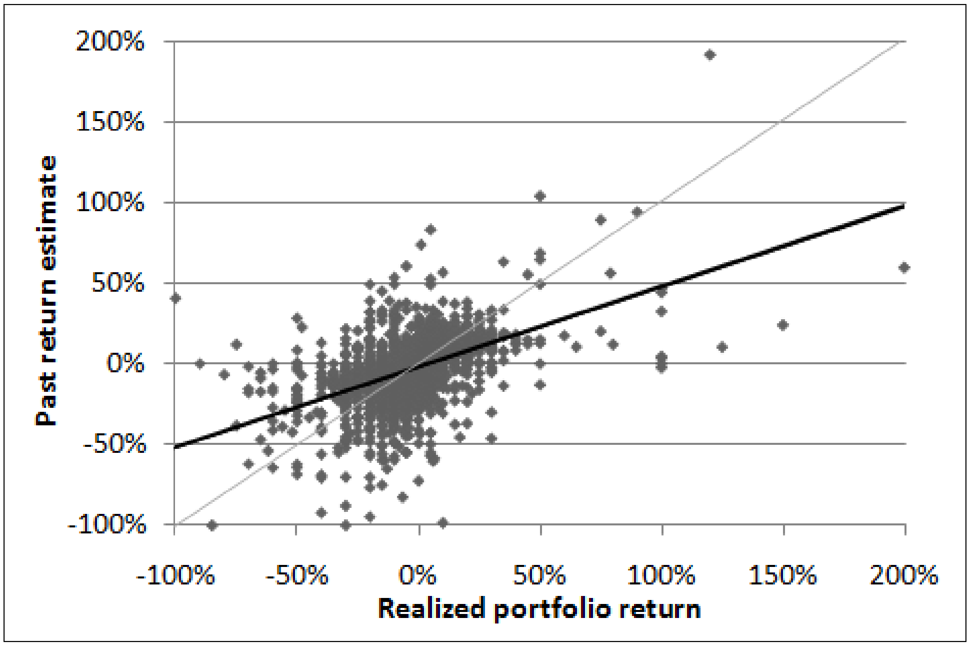
Notes: Average volatility estimates of survey participants and implied option volatility for the FTSE (right axis). Average level of miscalibration with implied volatility as a benchmark (left axis).

Figure 2: Return and risk expectations of investors



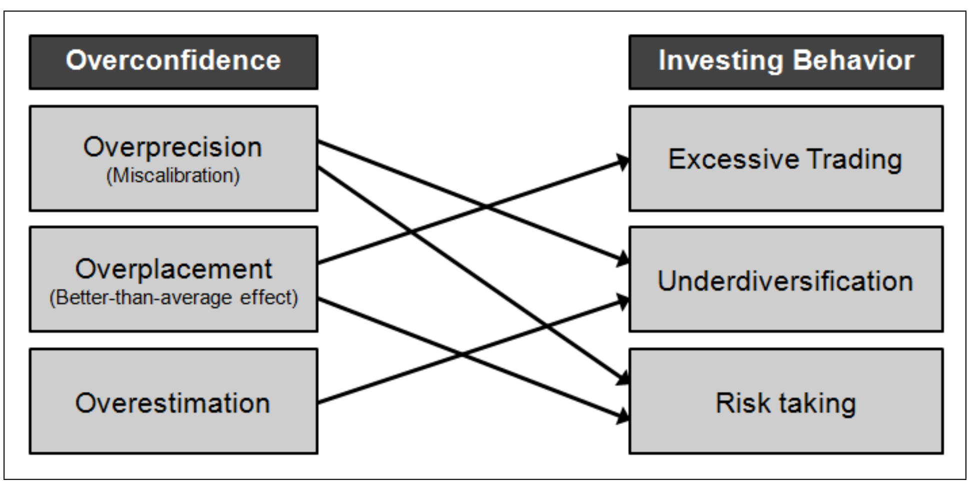
Notes: Average portfolio return expectations and market return expectations in % (left axis). Average risk perceptions for own portfolio and stock market on a seven-point scale (right axis).

Figure 3: Estimates and actual values for past portfolio return



Notes: The figure plots realized portfolio returns against (post-)estimates of portfolio return, including linear fitted values and 45-degree line.

Figure 4: Overconfidence and investing behavior



Notes: Types of overconfidence and their identified pathways to several aspects of investing behavior.