Network for Studies on Pensions, Aging and Retirement

Netspar DISCUSSION PAPERS

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How Return and Risk Experiences Shape Investor Beliefs and Preferences

DP 11/2012-044 (revised version September 26, 2013)

How Return and Risk Experiences Shape Investor Beliefs and Preferences

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This version: September 26, 2013

First version: December 10, 2011

Abstract: Beliefs and preferences drive investors' trading and risk-taking behavior, but what shapes their beliefs and preferences? Using a unique combination of brokerage records and matching monthly survey measurements, we examine how individual investors update their beliefs (return expectations and risk perceptions) and preferences (risk tolerance) in response to individual return and risk experiences. Past returns positively impact return expectations and risk tolerance, and negatively impact risk perceptions. Realized risk, however, does not impact investor beliefs and preferences. Investors' lack of awareness of realized risk is related to the complexity of standard risk measures, sophistication, and potentially the salience of return signals.

JEL Classification: D14, D81, D83, D84, G02, G11

Keywords: Individual Investors, Return Experiences, Risk Experiences, Investor Beliefs, Investor Preferences

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This research would not have been possible without the help of a large brokerage firm. The authors thank this broker for making available its data and its employees for answering numerous questions. For their comments on earlier drafts of this paper and helpful discussions, the authors thank Brad Barber, Jaap Bos, Jingjing Chai, John Chalmers, Prachi Deuskar, Simon Gervais, David Hirshleifer, Cars Hommes, Matti Keloharju, Marc Kramer, Christoph Merkle, Elias Rantapuska, Paul Smeets, Stefan Straetmans, Richard Taffler, Cesira Urzi, Mei Wang, and seminar and conference participants at the University of New South Wales, Maastricht University, the University of Amsterdam, the University of Münster, the Goethe-University Frankfurt, the Colloquium on Financial Markets at the Centre for Financial Research, the ZEW conference on The Role of Expectations in Financial Markets, the Netspar International Pension Workshop, the Boulder Summer Conference on Consumer Financial Decision Making, the Annual Meeting of the German Finance Association, the Annual Meeting of the Financial Management Association, the University of Sterling, the European Retail Investment Conference, the European Conference of the Financial Management Association, the Individual Finance and Insurance Decisions Centre, and the Tilburg Institute for Behavioral Economics Research (TIBER) Symposium on Psychology and Economics. Earlier versions of this paper circulated under the title "What Makes Investors Optimistic, What Makes Them Afraid?" The authors thank Donna Maurer for her editorial assistance. Any remaining errors are those of the authors.

1. Introduction

Beliefs and preferences are central determinants of individual investors' trading and risk-taking behavior, but what shapes their beliefs and preferences? This is an important question, because individual investor behavior affects asset prices (Lee, Shleifer, and Thaler 1991; Hirshleifer 2001; Kumar and Lee 2006; Kogan et al. 2006; Barber, Odean, and Zhu 2009), return volatility (Foucault, Sraer, and Thesmar 2011), and even the macro-economy (Korniotis and Kumar 2011a). We conduct a field study to examine how individual investors update their beliefs (return expectations and risk perceptions) and preferences (risk tolerance) in response to individual return and risk experiences. We base our analyses on a unique combination of brokerage records and matching monthly survey measurements of return expectations, risk perceptions, and risk tolerance, which have been shown to have predictive power for investors' actual trading and risk-taking decisions (Hoffmann, Post, and Pennings 2013a; 2013b). Return expectations reflect investors' optimism about their portfolios' returns; risk perceptions reflect investors' interpretations of the riskiness of their portfolios; and risk tolerance reflects investors' general attitude (like or dislike) toward financial risk.

We find that investors' past returns positively impact their return expectations and risk tolerance, and negatively impact their risk perceptions. That is, when updating beliefs and preferences, investors extrapolate recent return experiences. The risk of these past returns (as measured by their standard deviation), however, does not impact investors' return expectations, risk perceptions, or risk tolerance. Investors' lack of awareness of realized risk is related to the complexity of standard risk measures and investor sophistication, as well as potentially to the higher salience of return signals than risk signals (as return information is typically more readily available to individual investors than is risk information). Our findings complement prior literature on naïve reinforcement learning in 401 (k) savings decisions and IPO subscriptions, which suggests that investors extrapolate the gains that they have personally experienced (see Kaustia and Knüpfer 2008; Choi et al. 2009; Chiang et al. 2012). In particular, this literature focuses on how return and risk experiences impact investors' future behavior, such as the likelihood of participating in upcoming IPO auctions or increasing their 401 (k) savings rate. Extending this literature, we show how such experiences lead investors to update their beliefs and preferences, which precedes changes in their behavior. We do not find evidence that this updating process is compatible with a rational benchmark. Return and risk experiences influence beliefs and preferences consistent with predictions from a set of established and interrelated behavioral concepts comprising prospect theory, the representativeness heuristic, the affect heuristic, and the availability heuristic.

The results of this paper help explain important patterns observed in financial markets. In particular, the results improve our understanding of the psychological mechanisms driving mutual fund flows and fueling asset-price bubbles. Our results help explain why high fund returns increase fund flows, while realized risk has no impact, except for sophisticated investors (Sirri and Tufano 1998; Huang, Wei, and Yan 2012; Chalmers, Kaul, and Phillips 2013). Our results demonstrate that especially unsophisticated investors are relatively unaware of realized risk. Regarding asset-price bubbles, the experiments of Hommes et al. (2005; 2008) show that extrapolative expectations can trigger bubbles. In a similar vein, Barberis (2012) suggests that the representativeness heuristic might have led investors to form overly optimistic return expectations prior to the 2008–2009 financial crisis. The results of this paper provide field evidence for the existence of such conditions in financial markets.

This paper builds upon earlier experimental work and extends scant field evidence on how return and risk experiences drive updates in individual investor beliefs and preferences. Prior experimental literature indicates that both return and risk experiences are important in shaping investors' beliefs and preferences. This literature, however, provides mixed evidence for the directional impact of such experiences on individual investors' beliefs and preferences. Evidence on the hot-hand fallacy, for example, suggests that investors extrapolate recent return experiences into the future (Gilovich, Vallone, and Tversky 1985; De Bondt 1993; Johnson, Tellis, and Macinnis 2005), while the gambler's fallacy suggests that investors expect a reversal after good returns (Tversky and Kahneman 1971; Kroll, Levy, and Rapoport 1988). As another example of mixed experimental findings, De Bondt (1993) finds a positive relationship between past returns and risk perceptions, while Ganzach (2000) and Shefrin (2001) indicate a negative relationship between past returns and risk perceptions.

The mixed experimental evidence might result from such factors as the lack of a real decision context (see e.g., Slovic 1969; Kühberger, Schulte-Mecklenbeck, and Perner 2002) or the use of participant samples that may or may not actively invest in the stock market. Field evidence overcoming these inherent limitations of experimental approaches, however, focuses on the relation between past returns and return expectations, and typically uses index returns and/or index volatility as a proxy for individual experiences.

Dominitz and Manski (2011), Greenwood and Shleifer (2013), and Kaplanski et al. (2013) find a positive relation between past index returns and expected returns in household and investor survey data. In contrast, using an event study of investor behavior around September 11, Glaser and Weber (2005) find that return forecasts are higher after a major drop in share prices, suggesting a belief in mean-reversion. Malmendier and Nagel (2011) find a positive relationship between index returns and households' willingness to take risks. They attribute this relationship mostly to the positive impact of past returns on beliefs (return expectations), while acknowledging that past returns may affect preferences (risk tolerance). Because of data limitations, however, these authors cannot discriminate between the two channels through which past returns impact individuals' subsequent willingness to take risks. Backing out investor beliefs from option price data, Barone-Adesi, Mancini, and Shefrin (2013) find that past returns and risk are related to measures of aggregate market overconfidence that are associated with return expectations and risk perceptions. Malmendier and Nagel (2011) find no effect of realized index volatility on households' willingness to take risks, while Kaplanski et al. (2013) find in their household survey data that past index volatility is negatively related to individuals' index return expectations and positively to their index risk perceptions. Finally, Hoffmann et al. (2013b) provide suggestive evidence for a link between index return experiences and individual investors' return expectations, risk perceptions, and risk tolerance, but these authors do not examine these relationships further.

We provide field evidence on how individual return and risk experiences shape investor beliefs (return expectations and risk perceptions) and preferences (risk tolerance). To do so, we analyze a unique dataset that combines brokerage records and matching monthly direct survey measurements of the beliefs and preferences of a panel of active individual investors. In so doing, we contribute to the literature on how investors update their beliefs and preferences in three ways. First, we contribute by examining investors' individual return and risk experiences instead of proxying for such experiences by using index returns or volatility. Second, we contribute by testing in one study the impact of both return and risk experiences. Third, we contribute by analyzing in a single study not either preferences or beliefs, but both.

2. Literature and Hypotheses

In this section, we review prior literature, based on which we develop hypotheses about the expected impact of return and risk experiences on the updating process of investor beliefs and preferences. This literature is mostly experimental and primarily proposes behavioral theories underlying the updating process of beliefs and preferences. Considering that we examine individual investors, a behavioral perspective strikes us as an appropriate point of departure. We do, however, compare this behavioral perspective to a rational benchmark in Section 4.5.

2.1 Investor Beliefs: Return Expectations

Previous work on how individuals form and update forecasts suggests that return experiences can impact individual investors' expectations in two ways. On the one hand, investors might be susceptible to the gambler's fallacy, misinterpreting the law of averages (Tversky and Kahneman 1971; Kroll, Levy, and Rapoport 1988). In an investment context, this implies that after experiencing high returns, investors tend to expect below-average returns (Shefrin 2002). On the other hand, investors may believe in the continuation of what they perceive as trends in prices and thus believe in "hot" ("cold") hands after observing positive (negative) outcomes (Gilovich, Vallone, and Tversky 1985; De Bondt 1993; Johnson, Tellis, and Macinnis 2005). Accordingly, we formulate the following two alternative hypotheses about the impact of investors' return experiences on their subsequent return expectations:

H_{1a}: *Investors' return expectations are negatively related to their return experiences.*

H_{1b}: *Investors' return expectations are positively related to their return experiences.*

Both the gambler's fallacy and the belief in hot hands are attributed to the representativeness heuristic, which proposes that investors consider more representative events to be more likely (Kahneman and Tversky 1972). Based on the theoretical results of Rabin (2002) and Rabin and Vayanos (2010), and on interpreting Burns and Corpus's (2004) and Tyszka et al.'s (2008) experimental results in an investor context, investors update their return expectations in line with hypothesis H_{1a} (gambler's fallacy) when they perceive the process that generates returns to be random. Updating return expectations in line with hypothesis H_{1b} occurs when investors believe that returns are generated by personal investment skills (hot hands). Our analysis thus also sheds light on investor perceptions regarding the return-generating process.

Regarding the impact of individual investors' risk experiences on their return expectations, we build on prior literature on representativeness and the affect heuristic. Based on survey data, Shefrin (2001) argues that because of representativeness, individuals expect high returns from safe stocks and low returns from risky stocks. Using their affective associations with a company when forming beliefs about returns and risk, investors assume that "good" stocks are those issued by "good" companies and associate these with both high future returns and safety (Finucane et al. 2000; Statman, Fisher, and Anginer 2008). Experiments confirm the resulting cross-sectional negative correlation between expected returns and risk (Ganzach 2000). We extend this negative relationship to an intertemporal setting. We propose that to draw inferences about various assets' expected returns, investors use information on the realized risk of those assets (just as they use past return information to form their expectations about assets' future returns). The findings of Barone-Adesi et al. (2013) support this conjecture. That is, these authors back out aggregate market beliefs from option prices and show that realized risk negatively impacts an overconfidence measure that is associated with return expectations. Moreover, these authors document a negative relationship between expected returns and risk. Accordingly, we develop the following hypothesis about the impact of investors' risk experiences on their future return expectations:

H_2: Investors' return expectations are negatively related to their risk experiences.

2.2 Investor Beliefs: Risk Perceptions

Prior work offers two competing views about the impact of investors' return experiences on their future risk perceptions. In an experiment, De Bondt (1993) finds that investors' risk perceptions are positively related to past returns. According to this author, investors believe that "the mere fact that a stock goes up in price increases its 'downward potential'" (1993:

369). Ganzach's (2000) and Shefrin's (2001) work on affect and the role of representativeness in investors' cross-sectional assessments of the riskiness of stocks with good or bad returns, however, suggests a negative relationship between investors' return experiences and their risk perceptions. Kempf, Merkle, and Niessen-Ruenzi's (2013) experimental results support the conclusions of these two earlier studies. Moreover, in their study of aggregate market beliefs, Barone-Adesi et al. (2013) find that a measure of overconfidence that is related to risk perceptions is negatively related to past returns. Accordingly, we formulate two alternative hypotheses about the impact of investors' return experiences on their future risk perceptions:

H_{3a}: Investors' risk perceptions are positively related to their return experiences.

H_{3b}: Investors' risk perceptions are negatively related to their return experiences.

Considering the influence of investors' risk experiences on their risk perceptions, literature on the representativeness heuristic suggests that investors tend to think that risk experienced in the past is indicative of future risk (see e.g., Chen et al. 2007). Indeed, Kempf et al.'s (2013) experimental study finds such a positive relationship between a stock's realized risk and subjects' ensuing risk perceptions. Similarly, Barone-Adesi et al. (2013) find that an aggregate market measure of overconfidence that is related to risk perceptions is positively related to realized risk. We thus formulate the following hypothesis about the impact of investors' risk experiences on their risk perceptions:

H_4: Investors' risk perceptions are positively related to their risk experiences.

2.3 Investor Preferences: Risk Tolerance

Considering the impact of investors' return experiences on their risk tolerance, experimental evidence on the house-money effect (Thaler and Johnson 1990) shows that if individuals apply a quasi-hedonic editing rule under prospect theory preferences (meaning that they integrate losses with prior gains, but not with losses), they feel that they can afford to take more risk after experiencing an initial gain. Even if these individuals accumulate some losses later on, they still perceive themselves to be in the positive domain of prospect theory's value function. Thaler and Johnson (1990) find this behavior for the majority of their experiments' subjects. A minority of their subjects (30% to 40%, depending on the specific experiment), however, behaved according to "standard" prospect theory and displayed less risk tolerance after experiencing gains (and vice versa). Since it is not obvious which updating behavior is more likely in a sample of actual investors, we formulate two alternative hypotheses:

H_{5a}: Investors' risk tolerance is positively related to their return experiences.

H_{5b}: Investors' risk tolerance is negatively related to their return experiences.

Regarding the impact of investors' risk experiences on their risk tolerance, recent literature indicates that personal experiences of economic fluctuations can shape individuals' willingness to take risk. In particular, Malmendier and Nagel (2011) and Guiso et al. (2011) propose that bad risk experiences decrease investors' willingness to take risks by decreasing their risk tolerance. Hence, we formulate the following hypothesis regarding the impact of investors' risk experiences on their subsequent risk tolerance:

H_6: Investors' risk tolerance is negatively related to their risk experiences.

3. Data

We base our analyses on a dataset also used in Hoffmann et al. (2013a; 2013b). Hoffmann et al. (2013a) show how investor beliefs and preferences drive trading and risk-taking behavior, while Hoffmann et al. (2013b) describe how investors respond to the 2008-2009 financial crisis by changing their trading and risk-taking behavior as well as their beliefs and preferences. The current paper, in turn, assesses how individual return and risk experiences shape investor beliefs and preferences. The data consist of the brokerage records of 1,510 clients of the largest discount broker in the Netherlands, along with matching monthly survey data collected for these investors from April 2008 through March 2009. The characteristics of individual investors in the Netherlands are similar to those of U.S. individual investors, and studies in economics and finance increasingly use data of Dutch individuals (see e.g., Bauer, Cosemans, and Eichholtz 2009; Dimmock and Kouwenberg 2010; van Rooij, Lusardi, and Alessie 2011; von Gaudecker, van Soest, and Wengstroem 2011; Kaplanski et al. 2013). We use discount brokerage data, because they provide two advantages. First, as discount brokers do not offer advice, the investment transactions and survey responses reflect investors' own decisions and opinions. Second, discount brokerage is an important channel through which both U.S. and Dutch individuals invest in the stock market (Barber and Odean 2000; Bauer et al. 2009). As the sample period corresponds to a time of considerable market volatility, there is substantial variation in investors' beliefs and preferences, as well as in their portfolio returns and risk, which is beneficial for estimating the effect of investors' realized portfolio returns and risk on subsequent changes in their beliefs and preferences. Following Hoffmann et al. (2013a; 2013b), we exclude accounts of minors (< 18 years) and of those with an average portfolio value of less than €250, as well as accounts in the top 1% of annual trading volume, transaction frequency, or turnover distributions, leaving 1,376 accounts for analysis.

3.1 Brokerage Records

Brokerage records are available for investors who completed at least one survey during the sample period. A "record" consists of an identification number, a transaction date and time, a buy/sell indicator, the type of asset traded, the gross transaction value, and transaction commissions. The records also contain information on investors' daily portfolio balances, demographics such as age and gender, and their six-digit postal code. Based on this postal code, which is unique to each street (or parts of a street) in the Netherlands, and data retrieved from Statistics Netherlands (Central Bureau of Statistics), we assign income and residential house value to each investor.[1] Table 1 defines all variables. Table 2 shows descriptive statistics of all brokerage accounts available, as well as those for the subset of accounts belonging to clients who completed the survey in each month of the sample period.

[Tables 1 and 2 here]

A comparison with samples of discount brokerage clients used in other studies of investor behavior in the United States (Barber and Odean 2000; Barber and Odean 2002) shows that this study's sample of investors is similar in terms of age and gender, portfolio size, and turnover. Moreover, according to a report on Dutch retail investors by Millward-Brown (2006), the account values comprise the major share of investors' total self-managed wealth. As capital gains are not taxed in the Netherlands, tax-loss-selling plays no role in the sample.

3.2 Survey Design and Data Collection

At the end of each month between April 2008 and March 2009, a panel of the broker's clients received an email prompting them to complete an online survey. To develop the panel, we

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[1] Home-ownership rates in the Netherlands are high (67.5%, as of 2008 (Eurostat 2011)), as well as skewed toward wealthier households (Rouwendal 2007). Thus, it is likely that the assigned house values correspond closely to the value of the houses actually owned by investors in the sample.

sent an email invitation to 20,000 randomly selected clients in April 2008. Six months later, we sent a reminder to maintain a sufficient response rate. The response rate of 4% (for April 2008) is in line with those of comparable large-scale surveys (cf. Dorn and Sengmueller 2009). A possible concern is that the monthly variation of non-response (Table 2) might not be random. Hoffmann et al. (2013b) compare the investors that responded to the survey to the broker's overall investor population and also perform an analysis of the monthly variation of non-response. Robustness checks based on these comparisons show that the sample is not subject to non-random response problems. Another possible concern is that differences in response timing might affect the results. That is, the return expectations, risk perceptions, and risk tolerance of early versus late respondents might differ, because of quickly changing market conditions. As investors' responses to the survey are clustered within the first few days after each survey email was sent, it is unlikely that there is a response-time pattern in the data that could introduce a possible bias. Indeed, in robustness checks that exclude late respondents, Hoffmann et al. (2013b) show that response timing is unlikely to be a concern.

The survey elicited information on investors' return expectations, risk perceptions, and risk tolerance for each upcoming month (see Table 3). We use qualitative measures, as they have greater explanatory power for individual decision-making than numerical measures, which are frequently misunderstood by respondents (Wärneryd 1996; Kapteyn and Teppa 2011). In particular, compared to numerical measures, qualitative measures are often superior predictors of individual preferences among options with unknown outcomes (Windschitl and Wells 1996), as well as actual investment behaviors (Weber, Weber, and Nosic 2013).

[Table 3 here]

Return expectations reflect investors' optimism about the returns of their portfolios and are measured similar to the qualitative measure used in Weber et al. (2013). Risk perceptions reflect investors' interpretations of the riskiness of their portfolios and are measured as in Pennings and Wansink (2004). Risk tolerance reflects investors' general predisposition (like or dislike) toward financial risk and is measured following Pennings and Smidts (2000).

To ensure a reliable measurement instrument, we use multiple items (i.e., survey questions) per variable, include these items in the questionnaire in a random order, and use a mixture of regular- and reverse-scored items (Netemeyer, Bearden, and Sharma 2003). After adjusting for any reverse-scored items, the final survey measures are computed by equally weighting and averaging their respective item scores. Such measures perform at least as well as those using "optimally" weighted factor scores, but have the advantage of a readily interpretable absolute modal meaning (Dillon and McDonald 2001).

We calculate Cronbach's alphas to examine each variable's reliability (Cronbach 1951). Cronbach's alpha indicates the degree of interrelatedness among a set of items (i.e., survey questions) that together measure a particular variable (e.g., return expectations) and is expressed as a number between 0 and 1. For a variable to be called reliable, Cronbach's alpha should be above 0.7 (Hair et al. 1998). Our measurements of return expectations, risk perceptions, and risk tolerance are reliable, as Cronbach's alpha ranges between 0.71 and 0.89 for these variables. That is, the individual survey items within each survey measure pick up similar information.

Figures 1–2 show the evolution of investors' mean return expectations, risk perceptions, and risk tolerance during the sample period. The three survey measures fluctuate over time and most monthly changes are statistically significant. In particular, 10 of the 11 monthly changes in mean return expectations, 8 of the 11 monthly changes in mean risk perceptions, and 4 of the 11 monthly changes in mean risk tolerance are statistically significant (at the 5% level or better). Consistent with prior literature, return expectations change more frequently than risk perceptions and risk tolerance (Bateman et al. 2011; Sahm

2012; Weber, Weber, and Nosic 2013). The survey measures correlate well with similar measurements that are available for U.S. markets. In particular, the correlation between the monthly average values of this study's measure of return expectations and the current personal finances item in the University of Michigan Index of Consumer Sentiment is 0.68.

[Figures 1-2 here]

Information generated by the three survey measures is economically relevant, as Hoffmann et al. (2013a) show with the same data that these measures have predictive power for investors' actual trading and risk-taking decisions. That is, investors behave in a manner that is consistent with what they report in the surveys. For example, investors with higher return expectations are more likely to trade, investors that are more risk tolerant hold riskier portfolios, and investors that increase their risk perceptions lower their buy-sell ratios.

Finally, as each of the three survey measures predicts a different aspect of investors' behavior, they are distinct measurements. In particular, investors' return expectations, risk perceptions, and risk tolerance are all related to trading activity, but only their risk perceptions and risk tolerance are related to risk-taking behavior (Hoffmann et al. 2013a). Likewise, correlations between the survey measures are all far from unity (see Table 4).

[Table 4 here]

4. Test of Hypotheses

4.1 Main Results

We analyze how investors' return and risk experiences impact updates in their beliefs (return expectations and risk perceptions) and preferences (risk tolerance) (H_1-H_6). We run panel regressions with changes in return expectations, risk perceptions, or risk tolerance as the dependent variable. We include investors' past portfolio returns (calculated as the product of the daily relative changes in the value of their portfolio, taking into account transaction costs and portfolio in- and outflows) or realized portfolio risk (standard deviation of daily portfolio returns) as explanatory variables that capture their return experiences or risk experiences, respectively. With respect to investor time-invariant effects, we include gender, age, account tenure, income, average portfolio value, and house value as control variables. Prior literature indicates that these variables are related to investor overconfidence, sophistication, and experience, which are important drivers of individual investor behavior (Barber and Odean 2001; Dhar and Zhu 2006; Korniotis and Kumar 2011b) and could also affect the updating of their beliefs and preferences. We include time-variant controls (Derivatives, Traded, Turnover) to capture potential effects of trading activity on the survey measures (e.g., investors who trade more could expect higher returns [cf. Dorn and Sengmueller 2009]). Finally, we include month fixed effects to control for unobserved external factors that could impact both the survey measures and the risk and return variables (such as monthly variation in market returns). By including these controls, we can be confident about measuring the distinct effects of individual return and risk experiences on investor beliefs and preferences.[2]

Table 5 shows that individual investors' return expectations are positively related to their return experiences (H_{1b}). In a real decision context, investors thus update according to the hot-hand fallacy and expect trends to continue, consistent with the experimental evidence of De Bondt (1993) and Johnson et al. (2005). In contrast, we find no support for the gambler's fallacy. The extrapolative type of return expectations updating that we find suggests that investors believe that their personal investment skills, and not random events, drive their

[2] We include the average of the portfolio value instead of the time-variant monthly portfolio value, because the monthly value is highly correlated with investors' returns. Instead of using the per-postal-code assigned income and residential house value control variables, we alternatively estimate model specifications with three-digit postal-code fixed effects and two-way clustered standard errors (investor and postal code). Results are consistent with the current specification. Thus, unobserved location-specific factors other than income and house value (such as overall wealth, education, or information) do not explain our results. Likewise, results obtained with alternative specifications that include individual fixed effects support our main findings. Results of models that include both past returns and return standard deviation in one regression are also in line with our main findings.

returns (see Rabin 2002; Burns and Corpus 2004; Tyszka et al. 2008; Rabin and Vayanos 2010 and also the robustness check in Section 5.1).

Investors' risk perceptions are negatively related to their return experiences (H_{3b}). This finding suggests that investors think that experiencing good returns means they have selected good stocks, which they also believe to be safe (see e.g., Shefrin 2001). Finally, investors' risk tolerance is positively related to their return experiences (H_{5a}). This finding is consistent with Thaler and Johnson's (1990) experimental evidence on the house-money effect.

[Table 5 here]

Table 6 shows that investors' return expectations, risk perceptions, and risk tolerance are not impacted by their risk experiences. Thus, we find no support for H_2, H_4, or H_6. Taken together, the results, as presented in Tables 5 and 6, indicate that in a real decision context, individual past returns have an extrapolative impact on return expectations, risk perceptions, and risk tolerance, while the risk of these returns plays no role.

Our results on return experiences help answer a question that Malmendier and Nagel (2011) could not resolve; that is, do return experiences impact investors through a beliefs channel or through a preferences channel? We find evidence that return experiences impact investors through both beliefs (return expectations and risk perception) and preferences (risk tolerance). As investors' beliefs change more frequently (see Section 3.2) and by larger units (compare Figures 1 and 2, and the coefficient magnitudes for past returns in Table 5) than their preferences, however, the beliefs channel seems to be the more relevant channel.

Overall, one could interpret our findings as indicating that individual investors care mainly about the returns they achieve, and consider risk, after it is realized, to be irrelevant. Such an interpretation, however, is in stark contrast to prior experimental work finding that risk experiences typically do shape investor beliefs and preferences. Hence, it seems likely that investors' real decision context differs from a lab environment along important dimensions. Real markets, for example, might be more complex and provide investors with less information or noisier signals. If that is the case, more salient signals and information that is easier to understand and/or process should be more likely to impact investors' beliefs and preferences. Likewise, more sophisticated investors should be more likely to incorporate information on realized risk than less sophisticated investors. Finally, when trading with actual money in a real decision context, investors might act more rationally than predicted by the behavioral theories underlying the experimental literature on which we base our hypotheses. In Sections 4.2 – 4.5, we examine each of these possibilities.

[Table 6 here]

4.2 Signal Salience

According to Tversky and Kahneman's (1973) availability heuristic, the extent to which individuals incorporate information depends on the ease with which it comes to mind. Especially when attention is limited, salient information is absorbed more easily than less salient information (Hirshleifer and Teoh 2003; Barber and Odean 2008). If our finding that investors' return expectations, risk perceptions, and risk tolerance are driven by their return experiences, but not by their risk experiences, is related to the salience of these signals, we would expect investors who examine their portfolios more often to have a better idea about the risk they experience (i.e., they would be more likely to observe fluctuations in their portfolios, which would improve their ability to estimate the return standard deviation). Unfortunately, we do not have access to brokerage data about investors' login frequency. Therefore, we use investors' trading activity as a proxy for the frequency with which they examine their portfolios (i.e., assuming that investors' trading activity is related to looking at their portfolios, as buying or selling a security requires investors to login to the brokerage system). We run several regressions in which we interact indicators for trading activity (having traded, indicator variables for turnover quartiles) with past returns and realized risk. These regressions do not yield significant results. This may be because trading activity is an imperfect proxy for the frequency with which investors look at their portfolios or because trading activity is typically inversely related to investment skills (see e.g., Barber and Odean 2000; Grinblatt and Keloharju 2009; Graham, Harvey, and Huang 2009). That is, although investors who trade more frequently may look at their portfolios more often, they may also have inferior investment skills and be more prone to behavioral biases, which could include a tendency to ignore relevant portfolio information, such as the risk of their portfolio's returns.

We have further data on investors' ability to observe their portfolios and their returns. Based on a survey question that asks investors to report the sign of their past portfolio return, we find that investors with returns that are close to zero have difficulty reporting the correct sign. Investors with large positive or negative returns, that are potentially more salient, however, are better in reporting the correct sign of their return (for details see Section 5.3). Thus, salience seems to play some role in investors' ability to observe return and risk signals.

The latter result on signal salience also helps answer a puzzling question: Why do risk experiences not effectuate changes in most investors' risk perceptions and risk tolerance, while these two measures are significant predictors of investors' risk-taking (see e.g., Hoffmann et al. 2013a; 2013b)? Moreover, in the 401(k) plan data analyzed by Choi et al. (2009), both past returns and risk impact participant behavior (i.e., their savings rates). That is, when investors update their risk perceptions and risk tolerance, they seem to ignore their risk experiences, but when making investment decisions, investors apparently do incorporate information on risk. The underlying reason for this discrepancy might lie in the interface design of a typical brokerage system. When buying (or selling) a security, snapshot information on this security's past return and risk is automatically displayed to clients or is just a mouse click away. Thus, at this stage of the investment process, risk is salient. For the individual components of and/or the complete portfolio of an investor, however, such information is more cumbersome to retrieve. Generally, only information on past returns is readily available at this stage of the investment process. Moreover, the investor herself must look up the information on the realized risk of each portfolio component, and to determine the risk of the complete portfolio, she must make relatively complex calculations. For many individual investors, this may require too much effort. Thus, they rely primarily on easily available past return information, as predicted by the availability heuristic (Tversky and Kahneman 1973). This conjecture also helps to reconcile the seemingly conflicting evidence on 401(k) savings decisions documented by Choi et al. (2009). In their data, participants make only few decisions on their savings rate (over their three-year sample period, only 35% of plan members made one or more changes). Thus for those infrequent, but important decisions, individuals might exert more effort, and incorporate information on realized risk.

4.3 Return and Risk Experiences: Alternative Measures

In the previous analyses, we find that only return experiences drive updates in investors' beliefs and preferences, while the risk of these returns has no effect. This result suggests that investors care mainly about their returns, but not about the risk of these returns, as measured by their standard deviation. Such an interpretation, however, implicitly assumes that investors are able to calculate a fairly complex risk measure and find it relevant for their decisions. As this assumption might not hold for individual investors, we test several simple alternative risk measures. In addition, we test other well-known measures of risk-adjusted returns and risk.

As measures for risk-adjusted returns, we use the one-factor Alpha and the Sharpe ratio.[3] As alternative measures for realized risk, we use the one-factor Beta, the one-factor idiosyncratic volatility, and several downside risk measures (to which the simplest risk measures belong). Prior studies using qualitative surveys or numerical experiments argue that downside risk measures might capture individual investors' interpretation of risk better than do standard symmetric measures of risk, such as the standard deviation of returns. In particular, such studies find evidence that individual investors associate risk with the semivariance of returns, the probability of a loss or a return below a target return, and the potential for a large loss (Slovic 1967; Olsen 1997; Unser 2000; Veld and Veld-Merkoulova 2008; Vlaev, Chater, and Stewart 2009). We operationalize the latter two measures by calculating the monthly percentage of returns below a target return ("percent returns below target") and the average of the four largest negative daily returns in a given month ("average of 4 worst returns"). As the target return for calculating the semivariance (i.e., the semi-standard deviation) and the percent returns below target, we use either the return on the Dutch market index (AEX) or a return of 0%. Prior work finds these benchmarks to be the most relevant for individual investors (see e.g., Unser 2000; Veld and Veld-Merkoulova 2008).

With respect to the risk-adjusted return measures, we find that Alpha, like returns, is a strong driver of investor beliefs and preferences. Both variables are highly correlated (Pearson correlation coefficient between return and Alpha is 0.72), and thus they impact investors in a similar way (see Table 7, Panel A). The Sharpe ratio is relevant for investors' return expectations, but is not a significant predictor for their risk perceptions or risk tolerance (which is not surprising, because it combines returns with the complex measure standard deviation).

[3] We cannot estimate multi-factor alphas and betas because of limitations on the portfolio-holdings data. Daily market-value data at the portfolio level are available for all investors. Detailed portfolio component data, however, are available for only 30% of investors. But even in that case, only the name of the security, the indication of the asset class, and the historical purchase prices are available for each portfolio component.

[Table 7 here]

Realized systematic risk (Beta), idiosyncratic risk, and the semi-standard deviation of returns are not significant predictors of investor beliefs and preferences (see Table 7, Panel B). Relatively simple downside risk measures, such as the percentage of returns below a target return, and the average of an investor's four worst returns, however, are significant predictors of changes in investors' return expectations. In particular, the signs of these measures' coefficients are in line with hypothesis H_2: Both a larger percentage of returns that lie below the target return and a smaller average of the four worst negative returns (i.e., a larger negative number) decrease investors' return expectations.

Thus, only when we use simple, easy-to-understand, and easily calculated measures of downside risk that are very closely related to returns do we find an effect on investor beliefs.[4] That is, in that case, risk experiences have a negative impact on investor return expectations. This finding is consistent with Shefrin (2001), who documents that representativeness leads individual investors to expect high returns from safe stocks and low returns from risky stocks.

4.4 Investor Experience and Sophistication

Experience and sophistication are key characteristics influencing investor behavior (Agnew 2006) that could also affect the formation of investor beliefs and preferences. To examine the possible impact of these investor characteristics, we run the same regression models as before, but include interaction terms for past returns and realized risk with variables that prior literature shows to be proxies for investor experience and sophistication. In particular, we use interaction terms for derivatives trading (Bauer et al. 2009; Seru, Shumway, and Stoffman 2010), age (Korniotis and Kumar 2011b; Korniotis and Kumar 2013), account tenure (Seru et al. 2010), income (Dhar and Zhu 2006), and wealth, proxied by the combined value of an investor's portfolio and house (Vissing-Jorgensen 2003; Calvet, Campbell, and Sodini 2009; van Rooij et al. 2011).

The interactions with wealth and trading derivatives, and most of the interactions with age, account tenure, and income, are not significant and not reported. For the other interactions, Tables 8 and 9 report the coefficients for the main effect and interaction term.

[Tables 8-9 here]

The overall pattern of results indicates that investors who are more experienced (longer account tenure) and more sophisticated (not in the highest age quartile, within the highest income quartile) update their return expectations, risk perceptions, and risk tolerance in a way that reflects a weaker belief in trend continuation and personal investment skills as the driver of their returns, as well as a weaker house-money effect. At the same time, sophisticated investors are also less prone to looking at past returns alone. In particular, the risk tolerance of investors in the top 50% of the income distribution is hardly impacted at all by their past returns. That is, more sophisticated investors are almost not at all subject to the house-money effect. Similar moderating patterns appear for account tenure. Consistent with Korniotis and Kumar (2011b; 2013), investors that do not belong to the highest age quartile (and thus have higher cognitive skills), have a weaker tendency to extrapolate past returns into the future (Table 8). Most importantly, realized risk matters for more experienced investors: Investors with longer account tenure increase their risk perception after experiencing more risk (Table 9). This finding relates to the experimental evidence of Kempf et al. (2013), who suggest that

[4] Although closely related to returns, these risk measures do not simply pick up the earlier described effect of past returns. That is, even when we include past returns in the regression, the coefficients for both target return risk measures remain significant. For the measure average of investors' four worst returns, this is not the case.

financially sophisticated investors assess risk and returns more comprehensively than less sophisticated investors.

4.5 Rationality of Updates in Beliefs

Investors trading with real money might update their beliefs more rationally than predicted by the behavioral theories underlying the experimental literature from Section 2, on which we base our hypotheses. For example, although generally, on a monthly basis, returns are nearly unpredictable (Welch and Goyal 2008) while risk is predictable (Andersen et al. 2001), it could be rational for investors to extrapolate past returns (or risk) if in our sample past returns are informative for future returns (or risk). This could be the case if investors' returns exhibit momentum and/or investors learn from their past returns in the sense that increased return expectations reflect that they have gained knowledge about their personal investment skills. If (one of) these explanations holds true, it would be rationally justified for these investors to expect good returns to continue. To test these possibilities, we first check whether in our sample past returns are predictive of future returns or risk. We then test whether high return expectations (potentially indicating learning about personal investment skills) predict higher future returns (in which case investors' expectations would be rationally justified). We first regress current returns on past returns. We find a positive (0.026) but insignificant coefficient (p = 0.526) for past returns. The regression of current realized risk (standard deviation) on past returns yields a negative coefficient (-0.121), which is again insignificant (p = 0.228). When we run a regression of current returns on past return expectations, the effect is also insignificant (coefficient for past return expectations is 0.003, p = 0.385). Based on these results, we conclude that for the investors in our sample, past returns do not provide information on future returns or risk that would justify extrapolative expectations from past returns to future returns and risk.

As a final test on the rationality of investors' beliefs updating, we check whether in our sample past volatility predicts future volatility. When we regress current volatility on past volatility, the regression coefficient (0.755, $p = 0.000$) indicates that past volatility is indeed informative for current volatility. Thus, for a rational investor, we should expect to find an effect of realized volatility on risk perceptions, which, however, is not the case (see Sections 4.1 and 5.3).

All in all, in our sample, past returns do not predict future returns, while past volatility does predict future volatility. Ironically, however, regarding investor beliefs, past returns are believed to predict future returns, while realized volatility is not seen to predict future volatility. We thus do not find evidence that the updating process of investor beliefs is consistent with a rational benchmark.

5. Robustness Checks

5.1 Self-Attribution Bias

In Section 4, we interpret the extrapolative type of return-expectations updating as evidence that investors believe that their personal investment skills instead of random events drive their returns. We base this interpretation on the theoretical results of Rabin (2002) and Rabin and Vayanos (2010), and on experimental evidence presented in the studies of Burns and Corpus (2004) and Tyszka et al. (2008). The experimental evidence, however, is obtained outside the investment domain (these studies use, for example, roulette-wheel outcomes or shots of basketball players). To provide additional evidence that a belief in skill is at play in investors' return-expectations-updating process, we perform a robustness check. For this additional test, we rely on the fact that investors who are subject to the self-attribution bias credit good experiences to their personal skills, but bad experiences to factors beyond their control. As a consequence, we expect that these investors will update their return expectations, risk perceptions, and risk tolerance to a greater extent after positive than after negative experiences (Daniel, Hirshleifer, and Subrahmanyam 1998). To examine this possibility, we alternatively interact dummy variables indicating whether an investor has beaten the Dutch stock market index (AEX) or achieved a positive return with past returns. We do not find significant results for the interaction terms in the regressions of risk perceptions and risk tolerance on past returns and changes in past returns and therefore do not report these results. With respect to return expectations, however, we find significant effects: In the return expectation regression, the main effect of past returns is reduced from 0.469 to 0.167, while the interaction term of beating the index and past returns is 0.480, and the main effect of having beaten the index is 0.146 (compare Tables 5 and 10). Achieving returns that exceed the index increases return expectations more than does just achieving high returns. Alternatively, having achieved a positive return (main effect) significantly increases return expectations (Table 10). Hence, achieving a positive return leads investors to update their return expectations more strongly than achieving a negative return. Both results are consistent with self-attribution bias and thus a belief in personal skills driving investment returns.

[Table 10 here]

5.2 Alternative Time Horizons

In previous analyses, we test the impact of the last month's return and risk on changes in investor beliefs and preferences, finding that past returns are an important determinant thereof but that realized risk is not. There is no theory leading us to expect that one month is the exact time horizon that investors use when forming beliefs and preferences. Thus, in the following, we test the effect of using different time horizons for past returns and risk. In particular, we run the same regression models as in Section 4.1, but instead of using information on the returns and risk of the past month, we use information on the past 60, 20, and 10 days. Results obtained from these alternative specifications are consistent with the findings reported in Section 4.1: Past returns are an important predictor of investors' beliefs and preferences (Table 11), whereas risk is not (detailed results available upon request).

[Table 11 here]

This analysis provides some additional insights. In particular, the coefficients for past returns become more significant in the risk-perception regression for shorter time windows, while the opposite occurs for risk tolerance. These results complement Malmendier and Nagel's (2011) household evidence that more recent experiences matter more in the formation of beliefs (risk perception). Furthermore, these results extend Bateman et al.'s (2011) and Weber et al.'s (2013) finding that investors' preferences (risk tolerance) are relatively stable, in that we find that such preferences are impacted more by long-term experiences than by short-term ones.

5.3 Quality of the Survey Measures

As they form a central component of our data, we want to ensure the quality of the survey measures of investor return expectations, risk perceptions, and risk tolerance. A potential concern in this regard is that investors may not be aware of their return and risk experiences. In that case, changes in beliefs and preferences could be driven by unobserved factors instead of investors' actual return and risk experiences. For example, using a sample of discount brokerage clients, Glaser and Weber (2007) document that only about 61% of investors can accurately report the sign of their cumulative past return over a period of four years.

We have access to an additional survey question that allows us to directly check for potential problems in this regard. Specifically, from October 2008 through March 2009, investors responded to the following statement: "This month, I made a positive return." Investors' responses to this question were recorded on a seven-point Likert scale, ranging from 1 = totally agree to 7 = totally disagree, with the scale midpoint (category 4) labeled "neutral." We recode this survey variable into a new variable indicating whether investors correctly reported the sign of their return experience: Whenever an investor agreed with the statement (categories 1 to 3) and had a positive return or disagreed with the statement (categories 5 to 7) and had a negative return, we count this as a correct identification of the sign of the realized return; otherwise, we record an incorrect identification of the return sign.

It is not obvious how category 4 ("neutral") should be treated. To be conservative, we first treat all such responses as being in the incorrect sign category. Based on this conservative classification, 72.11% percent of investors correctly identify the sign of the return they realized over the past month. As an alternative classification, we exclude from the sample the responses in the "neutral" category, as well as observations where realized returns are very close to zero (between -1 and +1 percent). That is, we exclude those returns where it is likely that investors respond correctly or incorrectly just by accident. Based on this less conservative classification, 83.85% of investors give a correct response to the survey question. Thus, over a one-month time horizon, which is the primary focus of our analysis, most investors have a good idea of their performance in terms of the sign of their past returns.

In addition, we have supporting evidence from another survey variable, where we asked investors from October 2008 through March 2009 to report their number of transactions in the last month. The difference between the self-reported and the actual number of trades is only +0.14, on average, and statistically indistinguishable from zero (p-value = 0.77).

In conclusion, responses to both the sign of the past returns question and the last month's number of trades question indicate that most investors in the sample are well aware of their recent performance and trading activity.[5]

[5] We do not exploit the two survey variables further, as the limited number of responses (only from October 2008 through March 2009) results in a too-small sample size in the regression models of the main analysis.

Another potential concern with respect to the quality of the survey measures is that they are measured on a Likert scale that ranges from 1 to 7. Thus, investors that have responses at or close to the scales' upper or lower limit in a certain month might not be able to express updates in their beliefs and preferences for the next month appropriately. Hence, to test the robustness of the results, we exclude all observations where return expectation, risk perception, or risk tolerance values are smaller than 2 or larger than 6 and estimate the models of Section 4.1 again on the resulting subsample, which includes 84% of observations in the original sample. The results confirm the findings of Section 4.1: Past returns impact changes in beliefs and preferences in the same way as before (similar coefficient magnitudes and levels of significance), while we do not find an effect of realized risk on changes in beliefs and preferences (detailed results available upon request).

6. Conclusion and Discussion

Individual investor behavior influences asset prices, return volatility, and even the macro economy (Kumar and Lee 2006; Foucault, Sraer, and Thesmar 2011; Korniotis and Kumar 2011a). Important drivers of individual investor behavior are investors' beliefs (return expectations and risk perceptions) and preferences (risk tolerance) (Hoffmann et al. 2013a; 2013b). But what shapes investors' beliefs and preferences? Previous experimental studies provide mixed evidence of how individual investors form and update their beliefs and preferences in response to their individual return and risk experiences. The mixed experimental evidence might result from such factors as the lack of a real decision context (see e.g., Slovic 1969; Kühberger et al. 2002) or the use of participant samples that may or may not actively invest in the stock market. Only a few available field studies could potentially overcome the inherent limitations of existing experimental work, but these focus on the relation between past returns and return expectations, and typically use index returns and/or volatility as a proxy for individual experiences. We contribute to the existing literature by providing field evidence of the directional impact of both return and risk experiences on investor beliefs and preferences, using unique panel data from active individual investors.

We find that investors' return experiences are a powerful driver of their beliefs as well as preferences: Past returns positively impact return expectations and risk tolerance, and negatively impact risk perceptions. The risk of these past returns, however, is not related to changes in investors' return expectations, risk perceptions, or risk tolerance when examining standard risk measures, such as the standard deviation of returns. Investors' lack of awareness of realized risk is related to the complexity of standard risk measures, investor sophistication, and potentially to the higher salience of return signals than risk signals. When defining risk in terms of simple downside risk measures that are closely related to investors' past returns, we find a negative impact of risk experiences on return expectations. Moreover, the tendency to look primarily at past returns is pronounced among inexperienced and unsophisticated investors. These investors might find it difficult to evaluate and interpret portfolio risk, and instead use portfolio returns as a more easily available and salient performance metric.

Our findings complement prior work on naïve reinforcement learning, which suggests that investors tend to extrapolate the gains that they have personally experienced and shows how such extrapolation affects future investment behavior (see Kaustia and Knüpfer 2008; Choi et al. 2009; Chiang et al. 2012). Extending this literature, we show how return and risk experiences lead investors to update their beliefs and preferences. We do not find evidence that this updating process is compatible with a rational benchmark. Our results indicate that return and risk experiences influence investors' beliefs and preferences consistent with predictions from a set of established and interrelated behavioral concepts comprising prospect theory, the representativeness heuristic, the affect heuristic, and the availability heuristic. Moreover, our results extend the work of Malmendier and Nagel (2011), who find a positive relationship between return experiences and individuals' willingness to take risks, but could not distinguish whether the impact on risk taking is through beliefs (return expectations) or preferences (risk tolerance). Our results show that return experiences impact both the beliefs and preferences of individual investors.

The results of this paper improve our understanding of the psychological mechanisms driving mutual fund flows and fueling asset-price bubbles. First, regarding fund flows, our results help explain the stylized fact that past fund returns are positively related to fund flows, while past risk has no impact, except for sophisticated investors (Sirri and Tufano 1998; Huang et al. 2012; Chalmers et al. 2013). As past returns shape return expectations, risk perceptions, and risk tolerance, and these variables drive investors' trading and risk-taking behavior, past returns drive fund flows. As standard measures of past risk are not related to changes in return expectations, risk perceptions, and risk tolerance, however, and individual investors might find it difficult to understand risk, risk has no impact on fund flows.

Second, the extrapolative impact of past returns on subsequent changes in investor beliefs and preferences provides empirical evidence with respect to the psychological factors contributing to the creation of asset-price bubbles. The experiments of Hommes et al. (2005; 2008) show that such bubbles occur when individuals have trend-following expectations. Our results provide field evidence for the existence of these conditions in financial markets. In a similar vein, Barberis (2012) suggests that the representativeness heuristic might be responsible for investors' overly optimistic return expectation formation prior to the 2008–2009 financial crisis. Our results show that investors' return expectations indeed extrapolate return experiences. We thus provide empirical support for Barberis's theoretical perspective regarding the psychological factors that contribute to the creation of asset-price bubbles.

An intriguing question that remains is whether individual investors are able to learn more effectively from their experiences when given more time. In particular, do these investors eventually switch from a naïve to a more sophisticated form of reinforcement learning? And how does the length of confirming or contradicting experiences lead individuals to potentially switch between updating according to the gambler's fallacy or the belief in hot hands (see e.g., Bloomfield and Hales 2002; Rabin 2002; Asparouhova, Hertzel, and Lemmon 2009; Rabin and Vayanos 2010)? To answer such questions, we need a considerably longer sample period. Chiang et al. (2012) show in a study of IPO subscriptions that a lot of experience is needed for investors to start benefiting from it and that only a very small proportion of investors ever achieves the level of experience that is needed to learn more effectively. As a result, we will have to leave answering this question to future research.

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Table 1

Variable Definitions

Variable	Definition
Gender	Indicator variable taking the value 0 for male investors and 1 for female investors.
Age	Age of the investor in years as of April 2008.
Account Tenure	Account tenure of the investor in years as of April 2008.
Income	Annual disposable income in 2007 (equals gross income minus taxes, social security contributions, and health insurance premiums paid). Assigned to each investor based on her 6-digit postal code. This postal code is unique for each street in the Netherlands. Data source is the average net income per 6-digit postal code from Statistics Netherlands (Central Bureau of Statistics).
Portfolio Value	Value of the investment assets in an investor's account at the end of the month.
House Value	Value of the house in 2008. Assigned to each investor based on his or her 6-digit postal code. This postal code is unique for each street in the Netherlands. Data source is the average residential house value per 6-digit postal code from Statistics Netherlands (Central Bureau of Statistics).
Derivatives	Indicator variable taking the value 1 if an investor traded an option or futures contract at least once during a particular month; 0 otherwise.
Traded	Indicator variable taking the value 1 if an investor traded in a particular month; 0 otherwise.
Turnover	Average of the absolute values of all purchases and sales in a particular month, divided by the average of the portfolio values at the beginning and end of a particular month.
Return	Monthly investor return given by the product of the daily relative changes in the value of his or her portfolio after transaction costs and portfolio in- and outflows. For example, a monthly return of 10% takes the value 0.1 in the data.
Std(Return)	Investor-specific standard deviation of daily portfolio returns in a particular month (in monthly terms).
Alpha	One-factor alpha (Jensen's alpha) in a particular month (in monthly terms).
Beta	One-factor beta in a particular month.
Idiosyncratic Volatility	Standard deviation of the residuals in the one-factor model regression (in monthly terms).
Sharpe Ratio	Monthly return divided by the standard deviation of return (in monthly terms).
Semi-standard deviation (Index Return)	Standard deviation of daily portfolio returns below the target return in a particular month (in monthly terms). Target return is the return on the Dutch stock market index AEX.
Semi-standard deviation (Zero Return)	Standard deviation of daily portfolio returns below the target return in a particular month (in monthly terms). Target return is a return of 0%.
Percent Returns below Target (Index Return)	Monthly percentage of daily portfolio returns that are below the target return. Target return is the return on the Dutch stock market index AEX.
Percent Returns below Target (Zero Return)	Monthly percentage of daily portfolio returns that are below the target return. Target return is a return of 0%.
Average of 4 Worst Returns	Average of the four largest negative daily returns in a given month (in monthly terms).
Return Expectation	Reflects how optimistic a respondent is about his or her investment portfolio and its returns in the upcoming month. Details on the survey questions are given in Table 3.
Risk Perception	Reflects a respondent's interpretation of how risky the stock market will be in the upcoming month. Details on the survey questions are given in Table 3.
Risk Tolerance	Reflects a respondent's general predisposition toward financial risk. Details on the survey questions are given in Table 3.

Because of data availability, the data retrieved from Statistics Netherlands refer to different years, that is, to 2007 for income and to 2008 for house value.

Table 2

Descriptive Statistics

Panel A: All Brokerage Accounts													
Month		Apr-08	May-08	Jun-08	Jul-08	Aug-08	Sep-08	Oct-08	Nov-08	Dec-08	Jan-09	Feb-09	Mar-09
Investors	N	1,376	1,376	1,376	1,376	1,376	1,376	1,376	1,376	1,376	1,376	1,376	1,376
Gender	mean	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.08
Age	mean	50.56	50.56	50.56	50.56	50.56	50.56	50.56	50.56	50.56	50.56	50.56	50.56
	std	13.57	13.57	13.57	13.57	13.57	13.57	13.57	13.57	13.57	13.57	13.57	13.57
Account Tenure	mean	4.07	4.07	4.07	4.07	4.07	4.07	4.07	4.07	4.07	4.07	4.07	4.07
	std	2.77	2.77	2.77	2.77	2.77	2.77	2.77	2.77	2.77	2.77	2.77	2.77
Income €	mean	20,242	20,242	20,242	20,242	20,242	20,242	20,242	20,242	20,242	20,242	20,242	20,242
	std	4,314	4,314	4,314	4,314	4,314	4,314	4,314	4,314	4,314	4,314	4,314	4,314
Portfolio Value €	mean	52,854	52,695	44,872	42,840	45,963	37,688	31,127	30,100	30,679	29,564	26,514	27,875
	std	156,058	156,096	134,883	127,338	135,203	117,935	101,325	104,663	105,279	99,322	91,598	92,307
House Value €	mean	278,982	278,982	278,982	278,982	278,982	278,982	278,982	278,982	278,982	278,982	278,982	278,982
	std	112,278	112,278	112,278	112,278	112,278	112,278	112,278	112,278	112,278	112,278	112,278	112,278
Derivatives	mean	0.22	0.20	0.21	0.21	0.19	0.22	0.25	0.18	0.16	0.17	0.17	0.18
Traded	mean	0.46	0.47	0.48	0.47	0.41	0.51	0.63	0.42	0.37	0.41	0.40	0.42
Turnover (Traders)	mean	0.55	0.46	0.42	0.60	0.46	0.62	0.99	0.73	0.61	0.80	0.67	0.78
	std	1.53	1.22	1.12	1.85	1.41	1.87	3.63	1.82	1.82	2.77	2.49	2.46
Return	mean	0.03	0.00	-0.17	-0.10	0.05	-0.24	-0.23	-0.12	-0.04	0.00	-0.16	-0.01
	std	0.16	0.13	0.19	0.19	0.17	0.19	0.33	0.19	0.20	0.19	0.18	0.19
Std(Return)	mean	0.14	0.13	0.18	0.23	0.18	0.31	0.53	0.36	0.26	0.27	0.23	0.30
	std	0.25	0.23	0.29	0.33	0.28	0.36	0.42	0.37	0.32	0.32	0.32	0.35

Table 2

Descriptive Statistics – continued

		Panel B: Survey Respondents											
Month		Apr-08	May-08	Jun-08	Jul-08	Aug-08	Sep-08	Oct-08	Nov-08	Dec-08	Jan-09	Feb-09	Mar-09
Investors	N	787	701	605	557	520	491	650	402	330	312	272	291
Gender	mean	0.07	0.08	0.08	0.08	0.08	0.08	0.09	0.08	0.08	0.08	0.09	0.09
Age	mean	50.55	51.22	51.50	51.83	52.79	52.60	51.50	52.31	52.65	52.64	53.83	53.25
	std	13.51	13.55	13.43	13.57	12.90	13.05	13.29	13.25	12.88	12.86	12.62	12.67
Account Tenure	mean	3.93	3.98	4.09	3.98	4.11	4.08	4.26	4.35	4.34	4.45	4.53	4.38
	std	2.76	2.79	2.77	2.78	2.77	2.76	2.78	2.73	2.75	2.74	2.68	2.71
Income €	mean	20,181	20,088	20,109	19,978	20,085	20,002	20,147	19,892	19,859	20,046	20,034	20,028
	std	4,285	3,956	4,240	3,729	3,835	4,153	4,197	3,808	3,543	3,897	3,844	3,860
Portfolio Value €	mean	54,446	54,264	45,411	45,509	49,557	39,707	29,490	33,660	30,169	30,693	27,444	27,229
	std	143,872	144,617	128,455	128,159	124,176	105,507	100,216	118,529	66,600	66,198	53,089	55,039
House Value €	mean	276,690	272,969	272,038	273,559	274,221	274,736	277,543	272,429	272,020	273,443	277,193	273,037
	std	110,125	102,015	109,290	101,943	101,006	110,771	112,864	104,787	98,530	99,506	108,672	100,576
Derivatives	mean	0.24	0.23	0.25	0.25	0.23	0.24	0.26	0.19	0.20	0.24	0.22	0.20
Traded	mean	0.52	0.54	0.55	0.52	0.46	0.54	0.64	0.46	0.42	0.48	0.49	0.45
Turnover (Traders)	mean	0.65	0.43	0.49	0.57	0.36	0.50	1.10	0.86	0.47	0.56	0.70	1.00
	std	1.82	1.13	1.41	1.61	0.91	1.08	4.68	2.23	1.51	1.07	2.08	3.91
Return	mean	0.03	0.00	-0.18	-0.10	0.05	-0.25	-0.22	-0.12	-0.04	0.00	-0.17	-0.01
	std	0.17	0.12	0.18	0.18	0.20	0.18	0.34	0.19	0.16	0.20	0.20	0.21
Std(Return)	mean	0.15	0.13	0.18	0.23	0.18	0.31	0.53	0.37	0.26	0.28	0.25	0.32
	std	0.29	0.22	0.29	0.34	0.30	0.38	0.43	0.39	0.32	0.31	0.38	0.43
Return Expectation	mean	4.28	4.18	3.57	3.78	4.09	3.45	3.37	3.59	3.72	3.97	3.53	4.16
	std	0.94	0.92	0.96	0.97	1.00	1.06	1.04	1.10	0.99	1.09	1.17	1.06
Risk Perception	mean	4.49	4.44	5.00	4.15	3.97	4.45	4.27	4.26	4.24	4.18	4.44	4.24
	std	1.63	1.58	1.93	1.13	1.15	1.17	1.31	1.28	1.24	1.22	1.32	1.20
Risk Tolerance	mean	3.91	3.93	3.58	3.77	3.85	3.56	3.67	3.70	3.79	3.74	3.73	3.86
	std	1.19	1.11	1.25	1.19	1.18	1.30	1.33	1.26	1.18	1.20	1.28	1.14

This table presents monthly summary statistics for the brokerage account data. Panel A refers to all investors for whom brokerage records are available. This sample includes investors who participated at least once in the survey during the sample period, and who were not excluded by the sample-selection restrictions defined in Section 3. The monthly summary statistics presented in Panel B refer to the subset of investors who responded to the survey in each respective month. Variables are defined in Table 1.

Table 3

Survey Questions

Survey Variable	Answer Categories
Return Expectation (1 = low/pessimistic, 7 = high/optimistic)	
Next month, I expect my investments to do less well than desired.	1 (totally agree)–7 (totally disagree)
For the next month, I have a positive feeling about my financial future.*	1 (totally agree)–7 (totally disagree)
Next month, my investments will have a worse performance than those of most other investors.	1 (totally agree)–7 (totally disagree)
Next month, it is unlikely that my investment behavior will lead to positive returns.	1 (totally agree)–7 (totally disagree)
For the next month, the future of my investment portfolio looks good.*	1 (totally agree)–7 (totally disagree)
Risk Perception (1 = low perceived risk, 7 = high perceived risk)	
I consider investing to be very risky next month.*	1 (totally agree)–7 (totally disagree)
I consider investing to be safe next month.	1 (totally agree)–7 (totally disagree)
I consider investing to be dangerous next month.*	1 (totally agree)–7 (totally disagree)
I consider investing to have little risk next month.	1 (totally agree)–7 (totally disagree)
Risk Tolerance (1 = low risk tolerance, 7 = high risk tolerance)	
Next month, I prefer certainty over uncertainty when investing.	1 (totally agree)–7 (totally disagree)
Next month, I avoid risks when investing.	1 (totally agree)–7 (totally disagree)
Next month, I do not like to take financial risks.	1 (totally agree)–7 (totally disagree)
Next month, I do not like to "play it safe" when investing.*	1 (totally agree)–7 (totally disagree)

This table presents the questions used in this study's 12 monthly surveys. A 7-point Likert scale is used to record investors' response to each question. Each survey variable (return expectation, risk perception, risk tolerance) is calculated as the equally weighted average of the respective survey questions. * denotes a reverse-scored question.

Table 4

Correlations Between Survey Measures

	Return Expectation	Risk Perception	Risk Tolerance
Return Expectation	1		
Risk Perception	-0.34***	1	
Risk Tolerance	0.29***	-0.12***	1

This table presents the Pearson correlation coefficients between investor survey measures. Variables are defined in Table 1. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 5

Impact of Past Return on Changes in Survey Measures

Dependent Variable	Δ Return Expectation			Δ Risk Perception			Δ Risk Tolerance		
	Coef.	Std. err.		Coef.	Std. err.		Coef.	Std. err.	
Return	0.469	0.086	***	-0.223	0.133	*	0.186	0.110	*
Gender	0.053	0.039		-0.027	0.055		-0.015	0.041	
Age	0.001	0.001		-0.001	0.001		-0.001	0.001	
Account Tenure	-0.002	0.003		-0.002	0.005		0.003	0.004	
ln(Income)	0.014	0.088		0.095	0.161		-0.116	0.105	
ln(Avg. Portfolio Value)	-0.003	0.006		0.002	0.009		-0.006	0.007	
ln(House Value)	0.016	0.045		-0.040	0.074		-0.004	0.051	
Derivatives	0.017	0.041		-0.074	0.072		-0.050	0.050	
Traded	0.038	0.031		0.034	0.053		0.119	0.038	***
Turnover	0.029	0.012	**	-0.041	0.017	**	0.029	0.020	
Constant	0.144	0.586		-0.633	1.049		1.214	0.676	*
Time fixed effects	YES			YES			YES		
N Observations	3,955			3,955			3,955		
N Investors	1,045			1,045			1,045		
R^2	0.165			0.063			0.032		

This table presents the results from regressions of changes in investor return expectation, risk perception, or risk tolerance on past investor returns and a set of control variables. That is, we regress the monthly update of beliefs and preferences on the respective return experience in that month. The columns show results of linear panel models. The number of individual investors included in the regression (1,045) is smaller than the sample available for analysis (1,376) because not all investors responded to the survey for two consecutive months. Standard errors are clustered on the investor level. Variables are defined in Table 1. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 6

Impact of Past Risk on Changes in Survey Measures

Dependent Variable	Δ Return Expectation		Δ Risk Perception		Δ Risk Tolerance	
	Coef.	Std. err.	Coef.	Std. err.	Coef.	Std. err.
Std(Return)	-0.013	0.043	0.033	0.072	-0.001	0.054
Gender	0.055	0.038	-0.027	0.055	-0.014	0.041
Age	0.000	0.001	-0.001	0.001	-0.001	0.001
Account Tenure	-0.002	0.003	-0.003	0.005	0.003	0.004
ln(Income)	0.014	0.088	0.094	0.161	-0.116	0.105
ln(Avg. Portfolio Value)	0.004	0.006	0.000	0.009	-0.003	0.007
ln(House Value)	0.021	0.045	-0.043	0.074	-0.002	0.051
Derivatives	-0.017	0.041	-0.062	0.075	-0.064	0.051
Traded	0.031	0.031	0.036	0.053	0.116	0.038 ***
Turnover	0.017	0.012	-0.037	0.016 **	0.024	0.020
Constant	-0.816	0.591	-0.217	1.043	0.989	0.685
Time fixed effects	YES		YES		YES	
N Observations	3,955		3,955		3,955	
N Investors	1,045		1,045		1,045	
R^2	0.158		0.063		0.031	

This table presents the results from regressions of changes in investor return expectation, risk perception, or risk tolerance on the realized risk of investor returns (standard deviation of return) and a set of control variables. That is, we regress the monthly update of beliefs and preferences on the respective risk experience in that month. The columns show results of linear panel models. The number of individual investors included in the regression (1,045) is smaller than the sample available for analysis (1,376) because not all investors responded to the survey for two consecutive months. Standard errors are clustered on the investor level. Variables are defined in Table 1. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 7

Impact of Past Return and Risk on Changes in Survey Measures—Alternative Return and Risk Measures

Panel A: Impact of Past Performance

Dependent Variable	Δ Return Expectation			Δ Risk Perception			Δ Risk Tolerance		
	Coef.	Std. err.		Coef.	Std. err.		Coef.	Std. err.	
Alpha	0.410	0.086	***	-0.323	0.112	***	0.234	0.101	**
Sharpe Ratio	0.205	0.028	***	-0.062	0.047		0.029	0.037	

Panel B: Impact of Realized Risk

Dependent Variable	Δ Return Expectation			Δ Risk Perception		Δ Risk Tolerance	
	Coef.	Std. err.		Coef.	Std. err.	Coef.	Std. err.
Beta	-0.002	0.016		-0.030	0.029	-0.010	0.020
Idiosyncratic Volatility	0.009	0.059		0.059	0.094	0.004	0.073
Semi-Standard Deviation (Index Return)	-0.039	0.039		0.057	0.069	-0.072	0.061
Semi-Standard Deviation (Zero Return)	-0.045	0.042		0.041	0.068	-0.059	0.056
Percent Returns below Target (Index Return)	-0.683	0.142	***	0.264	0.249	-0.034	0.188
Percent Returns below Target (Zero Return)	-0.587	0.168	***	0.066	0.279	0.196	0.218
Average of 4 Worst Returns	0.135	0.081	*	0.037	0.152	0.029	0.107

This table presents the results from regressions of changes in investor return expectation, risk perception, or risk tolerance on alternative past investor return measures (Alpha, Sharpe ratio; Panel A), and alternative realized risk measures (Beta, idiosyncratic volatility, semi-standard deviation, percent returns below target, average of four worst returns; Panel B) and a set of control variables. That is, we regress the monthly update of beliefs and preferences on the respective return and risk experiences in that month. The columns show results of the same panel models previously used in Table 5, with alternative measures for past returns and risk. Each line reported refers to an alternative model specification (separate regression). All returns and risk variables are scaled to refer to monthly terms. Variables are defined in Table 1. Standard errors are clustered on the investor level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 8

Impact of Past Return on Changes in Survey Measures—Interactions with Investor Characteristics

Dependent Variable	Δ Return Expectation		Δ Risk Perception		Δ Risk Tolerance	
	Coef.	Std. err.	Coef.	Std. err.	Coef.	Std. err.
Return	0.413	0.093 ***	-0.190	0.146	0.140	0.117
Age > 75% * Return	0.258	0.154 *	-0.142	0.241	0.202	0.215
Return	0.435	0.088 ***	-0.159	0.143	0.351	0.111 ***
Account Tenure > 75% * Return	0.117	0.174	-0.214	0.245	-0.576	0.213 ***
Return	0.406	0.095 ***	-0.225	0.153	0.316	0.126 **
Income > 50% * Return	0.136	0.147	0.006	0.222	-0.278	0.162 *

This table presents the results from regressions of changes in investor return expectation, risk perception, or risk tolerance on past investor returns and a set of control variables. That is, we regress the monthly update of beliefs and preferences on the respective return experience in that month. The columns show results of the same panel models previously used in Table 5, while also including alternative interaction terms. In each regression model, only one interaction term (and the main effect of the respective indicator variables) is included at the same time. That is, each two-variable block reported refers to an alternative model specification (separate regression). Reported are the main effect of the respective return variable and the interaction effect. Interaction variables with percentages refer to the quartiles in the distribution of the respective variable in the investor sample. Other variables are defined in Table 1. Standard errors are clustered on the investor level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 9

Impact of Past Risk on Changes in Survey Measures—Interactions with Investor Characteristics

Dependent Variable	Δ Return Expectation		Δ Risk Perception		Δ Risk Tolerance	
	Coef.	Std. err.	Coef.	Std. err.	Coef.	Std. err.
Std(Return)	-0.005	0.044	0.023	0.078	0.022	0.055
Age > 75% * Std(Return)	-0.039	0.095	0.039	0.136	-0.105	0.113
Std(Return)	-0.007	0.052	-0.030	0.082	-0.034	0.062
Account Tenure > 75% * Std(Return)	-0.015	0.071	0.159	0.096 *	0.087	0.088
Std(Return)	-0.035	0.054	0.057	0.098	-0.024	0.062
Income > 50% * Std(Return)	0.044	0.070	-0.049	0.112	0.045	0.083

This table presents the results from regressions of changes in investor return expectation, risk perception, or risk tolerance on the realized risk of investor returns (standard deviation of returns) and a set of control variables. That is, we regress the monthly update of beliefs and preferences on the respective risk experience in that month. The columns show results of the same panel models previously used in Table 6, while also including alternative interaction terms (and the main effect of the respective indicator variables). In each regression model, only one interaction term is included at the same time. That is, each two-variable block reported refers to an alternative model specification (separate regression). Reported are the main effect of the respective return risk variable and the interaction effect. Interaction variables with percentages refer to the quartiles in the distribution of the respective variable in the investor sample. Other variables are defined in Table 1. Standard errors are clustered on the investor level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 10

Impact of Past Return on Changes in Return Expectation—Interactions with Zero Return Benchmark

Dependent Variable	Δ Return Expectation	
	Coef.	Std. err.
Return	0.167	0.110
Beaten	0.146	0.036 ***
Beaten * Return	0.480	0.183 ***
Return	0.285	0.110 ***
Positive	0.152	0.045 ***
Positive * Return	0.191	0.226

This table presents the results from regressions of changes in investor return expectation on past investor returns and a set of control variables. That is, we regress the monthly update of return expectation on the respective return experience in that month. The column shows results of the same panel model previously used in Table 5, while also including alternative interaction terms (and the main effect of the respective indicator variables). In each regression model, only one interaction term is included at the same time. That is, each three-variable block reported refers to an alternative model specification (separate regression). Reported are the main effect of the respective return variable, the main effect of the indicator variable, and the interaction effect. The indicator variable is Beaten (= 1 if past return is larger than the index (AEX) return; 0 otherwise) or Positive (= 1 if past return is positive; 0 otherwise). Other variables are defined in Table 1. Standard errors are clustered on the investor level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 11

Impact of Past Return on Changes in Survey Measures—Alternative Past Return Windows

Dependent Variable	Δ Return Expectation		Δ Risk Perception		Δ Risk Tolerance	
	Coef.	Std. err.	Coef.	Std. err.	Coef.	Std. err.
Return past 60 days	0.467	0.077 ***	-0.007	0.120	0.291	0.091 ***
Return past month (baseline)	0.469	0.086 ***	-0.223	0.133 *	0.186	0.110 *
Return past 20 days	0.460	0.080 ***	-0.296	0.122 **	0.056	0.098
Return past 10 days	0.452	0.069 ***	-0.241	0.105 **	0.063	0.082

This table presents the results from regressions of changes in investor return expectation, risk perception, or risk tolerance on past investor returns and a set of control variables. The columns show results of the same panel models previously used in Table 5, with alternative windows for past returns. Each line reported refers to an alternative model specification (separate regression). All returns are scaled to refer to monthly terms, except for the past 60 days regressions. Here, returns are scaled to two monthly terms and consistent with that scale, the dependent variable is the change in return expectation (or risk perception, risk tolerance) over the last two months. Variables are defined in Table 1. Standard errors are clustered on the investor level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

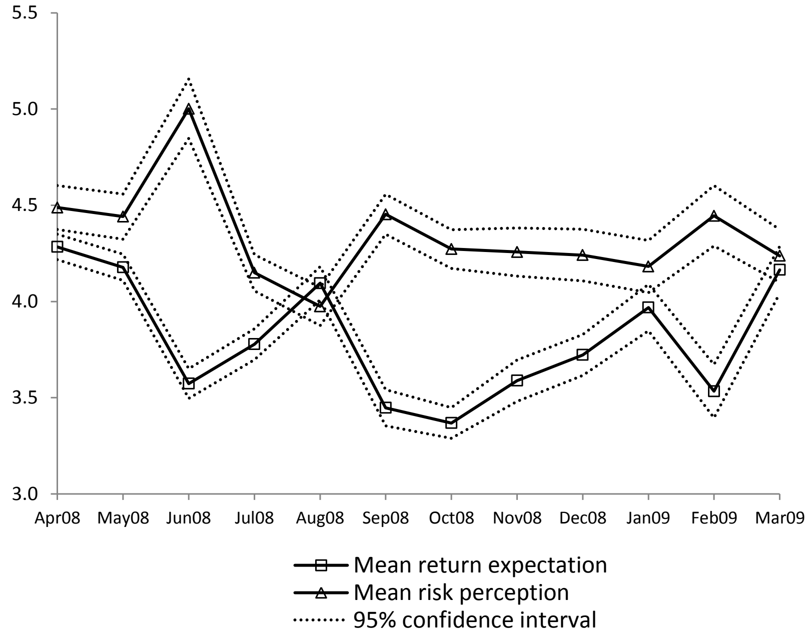

Figure 1. Investor Beliefs (Return Expectations and Risk Perceptions). Return expectations and risk perceptions are measured on a 7-point Likert scale (see Table 3). A small value indicates low return expectations or risk perceived, whereas a large value indicates high return expectations or risk perceived.

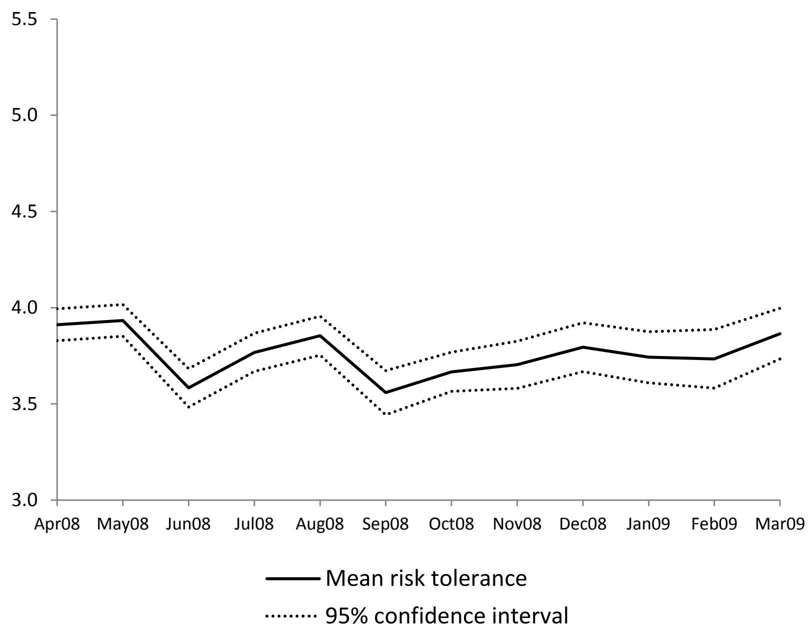

Figure 2. Investor Preferences (Risk Tolerance). Risk tolerance is measured on a 7-point Likert scale (see Table 3). A small value indicates low risk tolerance, whereas a large value indicates high risk tolerance.