How Does Investor Confidence Lead to Trading? Theory and Evidence on the Links between Investor Return Experiences, Confidence, and Investment Beliefs

Arvid O. I. Hoffmann*

Maastricht University and Netspar

Thomas Post

Maastricht University and Netspar

This version: September 30, 2013

Abstract: We develop a theory and present empirical evidence from a real trading environment on a mechanism through which investor confidence leads to trading. More confident investors rely more on intuitive judgments when forming beliefs about expected returns. In particular, they rely more on naïve reinforcement learning and extrapolate recent individual return experiences into the future more strongly. Because such return experiences are volatile, more confident investors change their beliefs more strongly, and thus have more reason to trade.

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

Keywords: Belief Formation, Investor Confidence, Naïve Reinforcement Learning, Return Experiences, Trading

* Corresponding author: Arvid O. I. Hoffmann, Maastricht University, School of Business and Economics, Department of Finance, P.O. Box 616, 6200 MD, The Netherlands. Tel.: +31 43 38 84 602. E-mail: a.hoffmann@maastrichtuniversity.nl.

This research would not have been possible without the help of a large brokerage firm. The authors thank this broker and its employees. For their comments on earlier drafts of this paper, the authors thank Sebastien Pouget, Stephan Siegel, and seminar and conference participants at the University of British Columbia, the University of Washington, and Maastricht University. The authors thank Donna Maurer for her editorial assistance.

How Does Investor Confidence Lead to Trading? Theory and Evidence on the Links between Investor Return Experiences, Confidence, and Investment Beliefs

Abstract: We develop a theory and present empirical evidence from a real trading environment on a mechanism through which investor confidence leads to trading. More confident investors rely more on intuitive judgments when forming beliefs about expected returns. In particular, they rely more on naïve reinforcement learning and extrapolate recent individual return experiences into the future more strongly. Because such return experiences are volatile, more confident investors change their beliefs more strongly, and thus have more reason to trade.

1. Introduction

It is a well-established finding that investors who are more confident trade more than investors who are less confident (see e.g., Barber and Odean 2001; Statman, Thorley, and Vorkink 2006; Glaser and Weber 2007; Grinblatt and Keloharju 2009). However, why do confident investors trade so much? This is an important question, as overtrading leads to underperformance through the accumulation of transaction costs (Barber and Odean 2000). The mechanism through which investor confidence results in more trading, however, remains unclear to date. We contribute to the literature by developing a theory and presenting empirical evidence on such a mechanism through which investor confidence leads to trading.

Typical explanations for the positive relationship between investor confidence and trading rely on theoretical models about how investors process and interpret information signals about firm fundamentals. More confident investors, for example, would believe more strongly in their private signals and/or overweight these signals when updating their beliefs (Odean 1998). The resulting divergence of opinion is hypothesized to lead to more trading by providing more reasons to trade. Generally, more confident investors are assumed to be more willing to act on their personal beliefs (Graham, Harvey, and Huang 2009; Deaves, Lüders, and Luo 2009). The present literature, however, typically assumes rather than empirically examines the mechanisms through which investor confidence translates into more trading. That is, so far the literature tests the ultimate relation between confidence and trading, but does not examine the intermediate stages explaining why confidence leads to trading.

Indeed, some of the assumed mechanisms on how confidence relates to trading appear ambiguous. For example, while the willingness to act on strong beliefs is expected to lead to (more) trading (Graham, Harvey, and Huang 2009), the opposite might be true as well. To elaborate, investors with strong beliefs might trade less, because those strong beliefs lead them to be less impacted by (or even be ignorant about) any new information they receive.

Moreover, existing models assume that investors possess relatively advanced information-processing capabilities and look primarily for signals on fundamental values. As a result, these models may be related only distantly to the reason why individual investors trade so often in reality. Indeed, Cochrane (2013: 44) states that “[m]odels in which an informed trader possesses a 'signal' about the value of a liquidating dividend just don’t describe the vast majority of trading. […] [M]ost […] traders […] look at patterns of prices, volumes, and past trading activity, not 'information' or opinion about firm fundamentals.”

We complement previous literature about the impact of investor confidence on trading behavior by developing a theoretical framework of investor belief formation and behavior in which investors—to varying degrees, depending on their confidence—take into account past prices (i.e., individual investment returns) when forming their expectations about future returns and subsequently trade based on those expectations. To conduct an empirical test of the predictions derived from our framework, we use a unique panel dataset that combines monthly survey data on investor expectations and confidence with matched trading records. We find that investors who are more confident about their investment beliefs (return expectations) display greater month-to-month updates in these beliefs. More confident investors thus change their opinions more strongly, and these changes lead to trading. Our results also show why confident investors change their opinions more strongly than less confident investors. Confidence relates to reliance on intuition and is associated with the use of cognitive shortcuts and heuristics. We find that more confident investors rely more on naïve reinforcement learning with respect to their return experiences. These investors extrapolate their recent return experiences into beliefs about future returns more strongly. Because such return experiences are volatile, more confident investors change their opinions more strongly, providing these investors with more reason to trade than less confident ones.

2. Theoretical Framework and Hypotheses

Our theoretical framework consists of four components: investor experiences, confidence, beliefs, and behavior (Figure 1). Investor experiences comprise individual-level past portfolio returns. In our framework, investors first observe their returns. Subsequently, based on these return experiences, investors form beliefs. That is, they update their return expectations. When updating their beliefs, investors extrapolate recent return experiences. That is, they rely on naïve reinforcement learning (also named the extrapolation heuristic (Chen et al. 2007; Kaustia and Knüpfer 2008; Choi et al. 2009; Chiang et al. 2012)). Finally, investors trade on their updated beliefs. Confidence enters the framework at the stage of belief formation. Investors' confidence level interacts with their interpretation of return experiences in that it leads them to rely more or less on naïve reinforcement learning when updating their beliefs.

[Figure 1 here]

Our theoretical framework is consistent with well-established findings from prior literature, while extending this literature by including the "experience-confidence-belief" intermediate link. Dominitz and Manski (2011), Malmendier and Nagel (2011), Greenwood and Shleifer (2013), and Hoffmann and Post (2012) find that return expectations depend on experienced returns. Consistent with naïve reinforcement learning, these studies find that recent experiences are extrapolated to expectations about future returns. That is, good past returns lead investors to form more optimistic expectations about future returns (and vice versa). Combining trading records and matching survey data on beliefs, Hoffmann et al. (2013a; 2013b) and Weber, Weber, and Nosic (2013) find direct evidence that updates in investor beliefs drive trading behavior.

Investor confidence is an important element in many theoretical models of investor beliefs and behavior. In Odean's (1998) seminal model, for example, investors receive (private) signals about a risky asset's fundamental value (which in our framework corresponds to individual-level information about past returns). In Odean's (1998) model, confident investors perceive a too-small variance of the signal when forming their beliefs, and thus have a different opinion on the attractiveness of the asset than less confident investors or investors not having received the signal. The resulting divergence in opinion provides reason to trade (Varian 1989; Harris and Raviv 1993; Banerjee 2011). Although investor confidence forms an important part of Odean's (1998) model, as well as related ones (see e.g., Kyle and Wang 1997; Daniel, Hirshleifer, and Subrahmanyam 1998; Benos 1998; Caballé and Sákovics 2003), its precise role is not tested empirically.

Furthermore, it is not evident whether the aforementioned mechanism through which investor confidence impacts trading behavior is an accurate description of reality. Numerous papers test the direct link between investor confidence and trading behavior (see e.g., Barber and Odean 2001; Statman, Thorley, and Vorkink 2006; Glaser and Weber 2007; Grinblatt and Keloharju 2009; Deaves, Lüders, and Luo 2009), but do not examine the underlying mechanism.[1] Moreover, recent studies doubt the realism of the mechanism linking investor confidence to trading behavior, as proposed by models such as that of Odean (1998). First, the average individual investor does not seem to possess private information about the fundamental value of assets (Coval, Hirshleifer, and Shumway 2005; Kaniel, Saar, and Titman 2008; Seasholes and Shu 2010; Døskeland and Hvide 2011). Second, individual investors may not look primarily at information about firm fundamentals, but instead at

[1] Based on the empirical result that, on average, individual investors accept negative returns on their trades (after considering potential trades for liquidity demands, tax-loss selling, portfolio rebalancing, move to lower-risk securities), Odean (1999) concludes that such trading behavior is consistent with overconfidence. Such behavior, however, may also be consistent with alternative trading motivations, such as trading for entertainment (Dorn and Sengmueller 2009).

patterns of past prices (see Cochrane 2013: 44), which is consistent with the naïve reinforcement learning of individual investors documented in the aforementioned literature.

Our framework complements previous theories about the impact of investor confidence on trading behavior and acknowledges the aforementioned doubts by incorporating signals that are easy for individual investors to observe and process. In particular, we use investor return experiences (past prices) as the trigger for belief formation. Our framework allows us to test empirically the mechanism through which investor confidence impacts belief formation. In our framework, investors update their beliefs (return expectations) by extrapolating recent return experiences. We propose that investor confidence is positively related to the strength of such naïve reinforcement learning. That is, given the same past return, more confident investors will extrapolate their return experiences to a greater extent.

In our framework, investor confidence relates to the notion of confidence, as described in Kahneman (2011: 212, 217). Accordingly, confidence about an investment belief (return expectations) is a feeling that reflects investors' mental construction of a coherent story that is not based on lengthy processes of reasoning, but instead is driven by quick and intuitive shortcuts. That is, investors rely on Dual Processing Theory's System 1 (System 2 is associated with slower and more effortful conscious reasoning).[2] Generally, the extent to which individuals rely on System 1, and thus base their judgments primarily on quick intuitive judgments, differs across individuals, but is relatively stable within them (Stanovich and West 2000; Evans 2003; Evans 2008; Alós-Ferrer and Hügelschäfer 2012). Thus, if investors' confidence refers to their degree of reliance on intuition, we expect the following:

H_1: Investor confidence is stable over time within investors.

[2] Evans (2003; 2008), Kahneman (2003), and Stanovich and West (2000) discuss Dual Process Theory in detail.

Prior research documents that individuals who base their judgments primarily on intuition tend to use more cognitive shortcuts and heuristics (Stanovich and West 2000; Evans 2003; Evans 2008). In particular, such individuals tend to rely more on naïve reinforcement learning (Alós-Ferrer and Hügelschäfer 2012). In line with this notion, Walther (2013) finds that confidence is positively correlated with relying on simple information search and decision strategies. Accordingly, we expect the following for investor belief formation:

H_2: More confident investors rely more on naïve reinforcement learning when updating return expectations.

Recent return experiences are volatile. For that reason, more confident investors relying more on naïve reinforcement learning will update beliefs by larger magnitudes. That is, we expect:

H_3: More confident investors change their return expectations more strongly.

H_3 provides the rationale for the positive link between investor confidence and trading: More confident investors change their beliefs more strongly, providing more reason to trade (Varian 1989; Harris and Raviv 1993; Banerjee 2011). Ultimately, as confident investors have more reason to trade, they trade more than less confident ones. That is, we expect:

H_4: Investors who change their return expectations more strongly have higher turnover.

3. Data

We base our analyses on a dataset also used in Hoffmann and Post (2012) and Hoffmann et al. (2013a; 2013b). The data comprise brokerage records of 1,510 clients of a large discount broker in the Netherlands and matching monthly survey data from April 2008 through March 2009. Individual investors in the Netherlands and the United States share similar characteristics, 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). Because these investors do not receive advice from the discount broker, the investment transactions and survey responses reflect their own decisions and opinions. As in 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

We have brokerage records of investors who completed at least one survey during the sample period. Apart from transaction information, the records contain information on investors' portfolio balances, demographics such as age and gender, and their six-digit postal code. Using data from Statistics Netherlands, we use this postal code to assign income and residential house value to each investor.[3] Table 1 defines all variables. Table 2 provides descriptive statistics of all brokerage accounts available, and those for the subset of accounts of clients who completed the survey in each particular month of the sample period.

[3] Home-ownership rates in the Netherlands are high (67.5%, as of 2008 (Eurostat 2011)) and skewed toward wealthier households (Rouwendal 2007), making it likely that the assigned house values correspond closely to the value of the houses actually owned by investors in the sample. Postal codes are unique to each street or even parts of a street in the Netherlands.

[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 Data

3.2.1 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 requesting them to complete an online survey. To develop the panel, we invited 20,000 randomly selected clients via email in April 2008. In October 2008, we sent a reminder email to these clients to maintain a sufficient response rate. The response rate of 4% (April 2008) is comparable to that of similar large-scale investor surveys (cf. Dorn and Sengmueller 2009). A possible concern is that the monthly variation in response rate (Table 2) is not random. To examine this notion, Hoffmann et al. (2013b) perform an analysis of the monthly variation in response rate and compare the investors who complete the survey to the broker's overall investor population. These comparisons show that the sample is not subject to non-random response problems. Another potential concern is response timing affecting the results. Beliefs and confidence of early versus late respondents might differ, because of changes in individual portfolio returns between their response times. As most responses are received within the first few days after we send each survey email, it is unlikely that there is a response-time pattern that could lead to a possible bias. In a check that excludes late respondents, Hoffmann et al. (2013b) show that response timing is indeed not a concern.

In our survey, we not only measure investors' return expectations and confidence therein, but also include measures on investors' risk perceptions and risk tolerance (as control variables). That is, we measure investors' beliefs (return expectations, risk perceptions), preferences (risk tolerance), and confidence in beliefs (regarding return expectations) for each upcoming month (Table 3). We use qualitative measures, because respondents tend to misunderstand quantitative measures. Qualitative measures also have greater explanatory power for individual decision-making (see e.g., Wärneryd 1996; Kapteyn and Teppa 2011). In particular, compared to quantitative measures, qualitative measures are often better predictors of individual preferences among options with unknown outcomes (Windschitl and Wells 1996) and individuals' actual investment behaviors (Weber, Weber, and Nosic 2013).

[Table 3 here]

3.2.2 Beliefs and Preferences

Return expectations depict investors' optimism about the returns of their investments and are measured in a similar way to that of Weber et al.'s (2013) qualitative measure. Risk perceptions gauge investors' interpretations of the riskiness of their investments and are measured as in Pennings and Wansink (2004). Risk tolerance reflects investors' predisposition (like or dislike) toward financial risk and is measured consistent with Pennings and Smidts (2000). To ensure that we measure investors' beliefs and preferences reliably, we use multiple items (i.e., survey questions) per variable, include these items in the questionnaire in a random order, and mix regular- and reverse-scored items (Netemeyer, Bearden, and Sharma 2003). After rescaling reverse-scored items, we compute the final survey measures by averaging their respective item scores.[4]

[4] 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).

To examine each variable's reliability, we calculate Cronbach's alpha (Cronbach 1951). Cronbach's alpha indicates the degree of interrelatedness among a set of items (i.e., survey questions) that measure a particular variable (e.g., return expectations). For a variable to be called reliable, Cronbach's alpha should be above 0.7 (Hair et al. 1998). Our measurements are reliable, as Cronbach's alpha ranges between 0.71 and 0.89 for the beliefs and preferences variables. The individual items within each survey measure thus pick up similar information.

The survey measures are cross-validated: Levels and changes in beliefs and preferences predict actual trading and risk-taking decisions (see Hoffmann, Post, and Pennings 2013a; 2013b). Finally, robustness checks in Hoffmann and Post (2012) show that most investors in the sample remember the sign of their portfolio returns correctly. Thus, the investors in the sample are aware of the returns they have experienced in their own portfolios.

3.2.3 Confidence

We measure confidence with qualitative survey items (Walther (2013) follows a similar approach). After each of the survey items for return expectations, we ask investors, "How confident are you about this answer?" (Table 3). The final confidence measure is calculated by averaging the responses to the five confidence questions. There is substantial variation in confidence across investors (Figure 2). On average, investors are relatively confident in their return expectations, as the mean (median) confidence is 5.44 (5.38). Figure 3 shows how the survey measures for return expectations and confidence vary over the sample period.

[Figures 2-3 here]

Graphically, there appears to be a negative co-movement between return expectations and confidence. The correlation between the two measures, however, is close to zero (Pearson correlation coefficient = –0.010, p-value = 0.427). That is, the confidence measure does not simply pick up return-expectation information (see related robustness checks in Section 5.2).

Our confidence measure describes a feeling which reflects that an investor constructed a coherent story in his or her mind (see Section 2). As such, it indicates investors' reliance on quick intuitive shortcuts when forming expectations about returns. Previous literature uses numerous measures of investor confidence (Moore and Healy 2008), the most important of which are overestimation (the tendency to expect higher returns than granted by the facts), overplacement (the tendency to believe that one will perform better than the average investor), and overprecision (the tendency to have confidence intervals that are too narrow, also called miscalibration). Tests in Section 5.2 show that, in terms of predicted investor beliefs and behavior, our confidence measure has the greatest overlap with overprecision confidence.

Consistent with previous studies (Barber and Odean 2001; Statman, Thorley, and Vorkink 2006; Glaser and Weber 2007; Grinblatt and Keloharju 2009), we find a direct effect of confidence on trading. That is, more confident investors have higher turnover. Investors with above-median confidence have 7.2 percentage-points higher turnover than investors with below-median confidence (p-value = 0.107), while investors in the highest confidence quartile have 10.3 percentage-points higher turnover than other investors (p-value = 0.049).

4 Results

4.1 Stability of Confidence over Time (H_1)

In this section we test hypothesis H_1, which conjectures that investor confidence is related to a certain type of individual (relying more or less on intuition), and thus is stable over time. First, we examine how the cross-sectional mean of confidence changes over time. Confidence varies from month-to-month, but not by large numbers, and in most cases not significantly.

The average of the 11 monthly absolute changes of confidence (measured on a scale from 1 to 7) is 0.1. Of the 11 changes, one is significant at the 1% level (August-September 2008), two are significant at the 5% level (October-November 2008, January-February 2009), and one is significant at the 10% level (May-June 2008) (see Figure 3). Second, we examine within-investor changes in confidence. We find a high correlation coefficient of 0.65 (p-value 0.000) between an investors' current month's confidence and her previous month's confidence. Supporting evidence is provided by sorting investors into deciles based on their confidence in the previous month and then calculating the average value of current month's confidence for each decile (see Figure 4). Figure 4 indicates that if an investor was in a high (low) confidence decile in the previous month, she is also more likely to have high (low) confidence in the current month. Moreover, a transition matrix (see Table 4) shows that transition probabilities are highest along the diagonal. Hence, we find evidence in support of hypothesis H_1: There is little, if any, fluctuation in average investor confidence over time, and there is distributional stability of confidence in the cross-section of investors over time.[5]

[Figure 4 here]

[Table 4 here]

4.2 Stronger Reliance of Confident Investors on Naïve Reinforcement Learning (H_2)

Next, we test whether more confident investors rely more on naïve reinforcement learning. That is, we examine whether compared to less confident investors, more confident investors extrapolate return experiences more strongly when updating their return expectations (H_2). We run three panel regressions with the change in return expectations from the end of the

[5] This result is consistent with the literature that tests the stability of other confidence measures (see e.g., Jonsson and Allwood 2003; Parker and Fischhoff 2005; Merkle 2013; Glaser, Langer, and Weber 2013).
.

previous month to the end of the current month as the dependent variable. We include investors' portfolio returns during the current month (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) to capture return experiences and continuous, or alternatively, discrete interactions with investor confidence at the end of the previous month, as explanatory variables. Regarding investor time-invariant effects, we include gender, age, account tenure, income, average portfolio value, and house value. These variables are related to investor sophistication and experience, which drive individual investor behavior (Barber and Odean 2001; Dhar and Zhu 2006; Korniotis and Kumar 2011) and could also affect the updating of their beliefs. Bauer et al. (2009) find that investors who trade derivatives score higher on a survey question measuring whether they invest as a hobby compared to investors who do not trade derivatives. Therefore, we include an indicator of derivatives trading (Derivatives) as a time-variant control capturing potential alternative trading motivations, such as entertainment (cf. Dorn and Sengmueller 2009). We include month fixed effects to control for unobserved factors that could impact both the survey measures and the return variable (such as monthly variation in market returns). By including these controls, we measure the distinct effects of individual return experiences and confidence on investor return expectations (see Table 5).[6]

[Table 5 here]

[6] 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 (available on request) 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.

In the first column of Table 5, we replicate the results obtained by Hoffmann and Post (2012), who document return-experience-based naïve reinforcement learning. In particular, the positive coefficient on experienced returns shows that investors extrapolate individual return experiences when updating their return expectations.[7] In the second column, we extend the model by including confidence at the end of the previous month, and an interaction of that variable with returns, as independent variables. The second column provides supporting evidence for hypothesis H_2: The interaction term of confidence and returns is positive and significant. When forming expectations about future returns, investors with higher confidence extrapolate recent return experiences more strongly.[8] An alternative specification with returns being interacted with a discrete dummy variable for high confidence (1 if confidence is larger than the 75% quartile, 0 otherwise) shows results that also support hypothesis H_2 (third column). In line with the results of Section 4.1 on the stability of confidence within investors, results do not differ substantially if we relate changes in beliefs alternatively to investor confidence in the current month (elicited at the end of the current month).[9] Consequently, when we regress levels of beliefs on investor confidence in an individual fixed-effects model as a third alternative set-up, the confidence and confidence return interaction terms are not significant (results available on request).

[7] Because we do not include the trading indicators D_Trade and Turnover as control variables (because of their relation to confidence), the coefficient on past return is slightly different than that in Hoffmann and Post (2012).

[8] The coefficient for past return becomes insignificant in this specification, but the three coefficients for past return, confidence, and the interaction term of both these variables are jointly significant at the 1% level (p-value = 0.000). The coefficient for past return is negative in this specification. Thus, investors with very low levels of confidence (below 2.89) would actually depict a reversed extrapolation bias. Only 0.73% of observations are below this threshold and thus such a reversed extrapolation bias has no empirical relevance.

[9] This also holds for the analyses testing hypotheses H_3 and H_4.

4.3 Confident Investors Change Their Return Expectations More Strongly (H_3)

Next, we analyze the link between confidence and absolute (non-directional) changes in beliefs. That is, we test hypothesis H_3, which predicts that more confident investors change their beliefs more strongly. Figure 5 plots the average of the absolute values of the changes in return expectations against previous month's confidence deciles. The figure suggests that investor confidence is positively related to the absolute magnitude of updates in beliefs.

[Figure 5 here]

Next, we test the significance of the relation of confidence and the absolute magnitudes of updates of return expectation (= ABS[Return Expectation$_t$ – Return Expectation$_{t-1}$]), using panel regressions with the same set of explanatory variable as those used in Section 4.2, but without including past return. That is, after having established the return-confidence-belief update link in Section 4.2, we now estimate the direct impact of investor confidence on the absolute magnitude of changes in their beliefs.

[Table 6 here]

Table 6 (left column) shows that investor confidence is positively and significantly related to the magnitudes with which investors update their return expectations. That is, we find support for hypothesis *H_3:* More confident investors change their beliefs more strongly, which ultimately gives them more reason to trade. Even when controlling for the standard deviation of returns in investors' portfolios (Table 6, right column), the effect of confidence on the magnitudes of updates in return expectations is significant. That is, higher magnitudes of updates by confident investors are not driven by more volatile return experiences (see the related robustness check in Section 5.2).

4.4 Investors Who Change Their Return Expectations More Strongly Have Higher Turnover (H_4)

Finally, we test whether investors who change their opinion more strongly also trade more, that is, have higher turnover (H_4). To test this hypothesis, we regress the turnover of investors that traded in a particular month (= Turnover_t) on the lagged absolute changes in return expectations (= ABS[$\text{Return Expectation}_{t-1}$ – $\text{Return Expectation}_{t-2}$]) and a set of control variables. That is, we examine the link between trading activity in a particular month and the magnitude of the absolute value of the update in return expectations over the preceding period.

[Table 7 here]

The results in Table 7 (left column) are consistent with the evidence in Hoffmann et al. (2013a; 2013b) and support hypothesis H_4: Investors who change their beliefs (return expectations) more strongly have higher turnover in the subsequent period. That is, stronger changes in beliefs provide more reason to trade. This result also holds when we control for investors' risk tolerance and risk perception (right column), ruling out the possibility that the effect of confidence on trading would not work through more confident investors' stronger updates in beliefs, but through risk tolerance and risk perception, which might relate to confidence and intuitive judgments (Dorn and Huberman 2005; Butler, Guiso, and Jappelli 2011a; 2011b).

Finally, Table 8 presents statistics on heterogeneity in investors' return experiences, changes in return expectations, and absolute changes in return expectations. These statistics highlight that within the cross-section of investors in each month, there is substantial variation in the magnitude of returns, the sign of returns achieved (positive or negative), the magnitude and direction of changes in return expectations, and the magnitude of absolute changes in return expectations. That is, next to changes in beliefs as one precondition of trading, we observe the second precondition for trading in the sample: There is substantial heterogeneity in the magnitude and direction of changes in beliefs. That is, there are differences in beliefs and changes in those differences (Varian 1989; Harris and Raviv 1993; Banerjee 2011). Investors with reasons to trade will thus be able to find a trading counterpart. Moreover, even if, occasionally, individual investors' changes in beliefs (and thus behavior) might be highly correlated, there is empirical evidence about rational traders in the market that absorb individual investor demand and supply. For example, firms tend to issue equity when stock markets perform well (Baker and Wurgler 2000; Schultz 2003; Baker and Wurgler 2009), thus absorbing correlated demand from individual investors.

[Table 8 here]

5. Robustness Checks

5.1 Rationality of Reliance on Naïve Reinforcement Learning

Our theoretical framework links investors' expectation formation to confidence, in that more confident investors rely more on naïve reinforcement learning, and thus extrapolate recent return experiences more strongly than less confident investors. Based on the same data, Hoffmann and Post (2012) show that, on average, extrapolating recent return experiences when forming return expectations is not rational in that it is associated with higher returns.

The return-generating process in the sample does not exhibit predictability or momentum, and return expectations do not contain information on investors' skill or subsequent performance. Investor confidence, however, might contain previously omitted information that is indeed related to depicting superior trading skill, so that it would be rational for more confident investors to extrapolate recent return experience more strongly compared to less confident investors. To examine this possibility, we regress investor returns on past return expectations, past confidence, and an interaction term for past return expectations with investor confidence.

Table 9 shows that neither past return expectations alone (first column), nor investor confidence and its interaction with return expectations (second column) are significantly related to investor returns. That is, investor confidence does not correlate with superior skills. If we exclude from the model variables that are related to investor confidence, that is, return expectations (related to confidence when forming beliefs) and trading indicators (related to confidence as more confidence triggers more trades through more strongly changing beliefs), investor confidence has a significant and negative effect on investor returns (third column). To conclude, it is not rational for more confident investors to extrapolate recent return experiences into the future more strongly. If anything, these investors' more strongly changing beliefs hurt their performance through higher turnover. Evaluating alternative performance measures (Sharpe Ratio, One-Factor Alpha) yield consistent evidence (available on request).

[Table 9 here]

5.2 Survey Measures: Reliability and Validity

To measure investors' return expectations, we use survey items that have already been used and cross-validated in previous studies (Hoffmann, Post, and Pennings 2013a; 2013b). In the context of the present study, however, the third survey item of the return expectation measure ("Next month, my investments will have a worse performance than those of most other investors") could be problematic. That is, because of the wording of the question, it could potentially already pick up investor confidence in its overplacement variant (the better-than-average effect). If this is the case, our finding that updates in return expectation are related to investor confidence might be driven by regressing similar pieces of information on each other. To check for this possibility, we rerun the main analyses, but now exclude this survey item when calculating the final measure for return expectations, as well the corresponding question for confidence when calculating the final measure for investor confidence. The results of this robustness check are consistent with the main results: Based on the newly calculated return expectations and confidence measures, the correlation coefficient of confidence with return expectations remains close to zero (Pearson correlation coefficient = –0.0538, p-value = 0.000), the correlation of the current month's confidence with the previous month's confidence remains high (Pearson correlation coefficient = 0.619, p-value = 0.000). Moreover, the coefficient of the continuous confidence interaction term with past returns in the changes in return expectation regression is positive (0.196) and significant (p-value = 0.015) (compare the original results in Table 5), the coefficient on confidence in the absolute changes in return expectation regression is positive (0.102) and significant (p-value = 0.000) (compare Table 6), and the coefficient on the lagged absolute changes in return expectations in the turnover regression is positive (0.086) and significant (p-value = 0.003) (compare Table 7).

In our theoretical framework, we link investor confidence with reliance on intuition and use of heuristics, as suggested by Kahneman (2011: 212, 217). Our results (stability of confidence, stronger reliance on heuristics by more confident investors) are consistent with such a link between confidence and intuition/heuristics, but we cannot test such a link directly with our data. Because we measure confidence in return expectations, it could be that something else other than reliance on intuition is linking confidence, return experiences, and return expectations. If, as we propose, confidence is a rather general characteristic of a person, then, it should also have relationships with other beliefs and preferences of investors that are driven by return experiences, even when confidence is measured in the context of return expectations. Hoffmann and Post (2012) find that not only return expectations, but also investors' risk perceptions and risk tolerance are driven by reliance on naïve reinforcement learning regarding past returns. If confidence is indeed something rather general, then investors who are more confident about their return expectations, and display greater updates in those expectations, should also display greater updates in their risk perceptions and risk tolerance. To check for this possibility, we regress the absolute changes in risk perception or risk tolerance on past confidence with the same set of control variables as those used in the return expectation regression in Section 4.3. We find a significant and positive impact of confidence on the magnitude of changes for both risk perceptions and risk tolerance. The coefficient for confidence in the risk perception regression is 0.092 (p-value 0.000) and in the risk tolerance regression it is 0.090 (p-value 0.000) (compare return expectation results in Table 6). Thus, although confidence is measured with respect to return expectations, it seems to reflect something more general as it interacts in a consistent way with the updating process of risk perceptions and risk tolerance.

In general, the confidence measures used in previous work are usually elicited by numerical survey questions (prediction tasks) (see e.g., Glaser and Weber 2007). Because we do not have corresponding questions in our survey, we cannot identify precisely if and to which of the previously used confidence measures our measure is most closely related. Based on the predictions of the effect of confidence on beliefs and behavior that differ between the three types of confidence, however, we can check to see with which measure our measure overlaps most closely. In particular, overestimation confidence predicts that return expectations are higher for more confident investors without being justified by higher returns. Overplacement confidence predicts that investors with high confidence expect to achieve higher returns relative to other investors. Overprecision (i.e., miscalibration) confidence predicts that investors with more confidence hold riskier portfolios than those that would be granted by their beliefs (return expectations, risk perception) and preferences (risk tolerance). We can test these predictions with the data available. First, we can rule out overestimation confidence because of the zero correlation reported in Section 3.2.3 between return expectations and confidence, and the fact that more confident investors do not achieve higher returns (see robustness checks in Section 5.1). Second, with respect to overplacement, we can exploit survey item number three for return expectations (compare Table 3), which reads "Next month, my investments will have a worse performance than those of most other investors." If our confidence measure is related to overplacement, then the correlation of confidence with this return-expectation item should be positive (as it is a reverse-scored item). The correlation of the third return-expectation item with our confidence measure is 0.080 (p-value 0.000).[10] Although the correlation is not large, this result is generally consistent with overplacement confidence. To check for overprecision confidence, we regress investor portfolio risk (standard deviation) on lagged confidence, while controlling for lagged beliefs (return expectations, risk perception) and preferences (risk tolerance), and the set of controls discussed in Section 4.1. Results in Table 10 show that our confidence measure is

[10] Alternatively, we calculate the correlation between our confidence measure excluding its third item or only

significantly related to higher portfolio risk, even after controlling for investor beliefs and preferences. This evidence is consistent with predictions from overprecision confidence.

[Table 10 here]

Thus, based on these results, we cannot discriminate between overplacement and overprecision confidence. We do have data from a 2006 survey with the same broker, however, where investors were asked to rate their competence as investors by self-categorizing as a "novice investor," "advanced investor," or "very advanced investor" (see Hoffmann and Shefrin (2013) for details on this survey). Based on the results of Graham et al. (2009), investor perceived competence is positively related to overplacement confidence. Thus, if our measure relates to overplacement rather than overprecision, we expect a positive relationship between confidence and self-rated competence. Matching survey respondents of the 2006 survey with current-survey respondents yields 245 investors for whom we have information on both self-categorized competence and confidence. In this subset of the data, average confidence for the investors does not increase with competence. The average of confidence is 5.50 for the "novice" group, 5.31 for the "advanced" group, and 5.44 for the "very advanced" group. Differences between the groups are not statistically significant. Based on the test results, we conclude that behavioral effects of our confidence measure overlap the most with predictions of overprecision confidence. In consequence, the direct overprecision-trading links found in prior empirical literature (see e.g., Deaves, Lüders, and Luo 2009) may stem from the mechanism identified in this paper and not the theoretical mechanism proposed in Odean (1998). Alternatively, both mechanisms may be linking overconfidence and trading simultaneously. In any case, the overlap of our measure with

---

the third item with the third return expectation item. In both cases we have correlations of similar magnitude (0.083 or 0.073), that are both significant (p-value 0.000).

predictions from overprecision suggest that both confidence dimensions potentially have their roots in the same mental processes, like reliance on intuition and System 1 activation.

A final 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 return expectations for the next month or confidence therein appropriately. Hence, to test the robustness of the results, we exclude all observations for a particular month where return expectations or confidence values are smaller than 2 or larger than 6 in the respective previous month and estimate the models of Section 4 again on the resulting subsample. The results confirm the findings of Section 4: Within investors, confidence is stable over time, while more confident investors rely more on naïve reinforcement learning and exhibit larger absolute updates of their return expectations (detailed results available upon request).

6. Conclusion and Discussion

Although it is well-known that more confident investors trade more, much less is known about the actual mechanism that links investor confidence to trading. Previous research proposes several such mechanisms, but does not test them empirically. More confident investors, for example, would believe more strongly in their private signals and/or overweight these signals when updating their investment beliefs (Odean 1998). The resulting divergence of opinion would lead to more trading. More confident investors also would be more willing to act on their personal beliefs (Graham, Harvey, and Huang 2009; Deaves, Lüders, and Luo 2009). The literature, however, mostly tests the ultimate relation between investor confidence and trading, but not the intermediate stages explaining why confidence leads to more trading.

We complement the literature on investor confidence by developing a theory and presenting empirical evidence on a mechanism through which confidence leads to trading. Our theoretical framework relies on well-established findings from prior literature, while providing an innovation by including an “experience-confidence-belief” intermediate link. In our framework, investors observe their returns. Based on these return experiences, they form beliefs about future returns (return expectations). When updating their beliefs, investors extrapolate recent return experiences. Confident investors rely more on this naïve reinforcement learning. Because recent individual return experiences are volatile, confident investors change their beliefs more strongly, and thus have more reason to trade.

Our results have potential implications for developing smart defaults, frames, or nudges that might attenuate individual investors’ tendency to have high portfolio turnover. Previous literature finds that, for example, manipulating portfolio evaluation periods or information aggregating levels can affect investors’ beliefs and behavior (see e.g., Gneezy and Potters 1997; Benartzi and Thaler 1999; Gneezy, Kapteyn, and Potters 2003; Looney and Hardin 2009; Beshears 2013). Accordingly, especially more confident investors might benefit from displaying their return experiences in a way such that they appear less volatile, which would potentially lead to smaller updates in these investors’ beliefs, and thus give them less reason to trade.

References

Alós-Ferrer, C. and S. Hügelschäfer (2012), "Faith in Intuition and Behavioral Biases," *Journal of Economic Behavior and Organization*, 84(1), 182-92.

Baker, M. and J. Wurgler (2000), "The Equity Share in New Issues and Aggregate Stock Returns.," *Journal of Finance*, 55(5), 2219-57.

Baker, M. and J. Wurgler (2009), "Under New Management: Equity Issuance and the Attribution of Past Returns," *working paper (Harvard University)*.

Banerjee, S. (2011), "Learning from Prices and the Dispersion in Beliefs," *Review of Financial Studies*, 24(9), 3025-68.

Barber, B. M. and T. Odean (2000), "Trading is Hazardous to Your Wealth: the Common Stock Investment Performance of Individual Investors," *Journal of Finance*, 55(2), 773-806.

Barber, B. M. and T. Odean (2001), "Boys Will be Boys: Gender, Overconfidence, and Common Stock Investment," *Quarterly Journal of Economics*, 116(1), 261-92.

Barber, B. M. and T. Odean (2002), "Online Investors: Do the Slow Die First?," *Review of Financial Studies*, 15(2), 455-87.

Bauer, R., M. Cosemans, and P. M. A. Eichholtz (2009), "Option Trading and Individual Investor Performance," *Journal of Banking and Finance*, 33(4), 731-46.

Benartzi, S. and R. H. Thaler (1999), "Risk Aversion or Myopia? Choices in Repeated Gambles and Retirement Investments," *Management Science*, 45(3), 364-81.

Benos, A. (1998), "Aggressiveness and survival of overconfident traders," *Journal of Financial Markets*, 1(3), 353-83.

Beshears, J. (2013), "Does Aggregated Returns Disclosure Increase Portfolio Risk-Taking?," *working paper (Stanford University)*.

Butler, J. V., L. Guiso, and T. Jappelli (2011a), "The Role of Intuition and Reasoning in Driving Aversion to Risk and Ambiguity," *working paper (Einaudi Institute for Economic and Finance)*.

Butler, J. V., L. Guiso, and T. Jappelli (2011b), "The Role of Intuition and Reasoning in Driving Aversion to Risk and Ambiguity ," *CEPR Discussion Paper No.DP8334*.

Caballé, J. and J. Sákovics (2003), "Speculating against an overconfident market," *Journal of Financial Markets*, 6(2), 199-225.

Chen, G., K. A. Kim, J. R. Nofsinger, and O. M. Rui (2007), "Trading Performance, Disposition Effect, Overconfidence, Representativeness Bias, and Experience of Emerging Market Investors," *Journal of Behavioral Decision Making*, 20(4), 425-51.

Chiang, Y-M, D. Hirshleifer, Y. Qian, and A. E. Sherman (2012), "Do Investors Learn from Experience? Evidence from Frequent IPO Investors," *Review of Financial Studies*, 24(5), 1560-89.

Choi, J., D. Laibson, B. Madrian, and A. Metrick (2009), "Reinforcement Learning and Savings Behavior," *Journal of Finance*, 64(6), 2515-34.

Cochrane, J. H. (2013), "Finance: Function matters, not Size," *Journal of Economic Perspectives*, 27(2), 29-50.

Coval, J. D., D. Hirshleifer, and T. Shumway (2005), "Can Individual Investors Beat the Market?,".

Cronbach, L. J. (1951), "Coefficient Alpha and the Internal Structure of Tests," *Psychometrika*, 16(3), 297-334.

Daniel, K. D., D. Hirshleifer, and A. Subrahmanyam (1998), "Investor psychology and security market over- and under-reactions," *Journal of Finance*, 53(6), 1839-85.

Deaves, R., E. Lüders, and G. Y. Luo (2009), "An Experimental Test of the Impact of Overconfidence and Gender on Trading Activity," *Review of Finance*, 13(3), 555-75.

Dhar, R. and N. Zhu (2006), "Up Close and Personal: Investor Sophistication and the Disposition Effect," *Management Science*, 52(5), 726-40.

Dillon, W. R. and R. McDonald (2001), "How to Combine Multiple Items into a Composite Score," *Journal of Consumer Psychology*, 10(1/2), 62-4.

Dimmock, S. G. and R. Kouwenberg (2010), "Loss-Aversion and Household Portfolio Choice," *Journal of Empirical Finance*, 17(3), 441-59.

Dominitz, J. and C. F. Manski (2011), "Measuring and Interpreting Expectations of Equity Returns," *Journal of Applied Econometrics*, 26(3), 352-70.

Dorn, D. and G. Huberman (2005), "Talk and Action: What Individual Investors Say and What They Do," *Review of Finance*, 9(4), 437-81.

Dorn, D. and P. Sengmueller (2009), "Trading as Entertainment?," *Management Science*, 55(4), 591-603.

Døskeland, T. M. and H. K. Hvide (2011), "Do Individual Investors Have Asymmetric Information Based on Work Experience?," *Journal of Finance*, 66(3), 1011-41.

Eurostat (2011), "Distribution of Population by Tenure Status, Type of Household and Income Group," *retrieved from* http://appsso.eurostat.ec.europa.eu/nui/show.do?dataset=ilc_lvho02&lang=en.

Evans, J. S. B. T. (2003), "In Two Minds: Dual-Process Accounts of Reasoning," *Trends in Cognitive Sciences*, 7(10), 454-9.

Evans, J. S. B. T. (2008), "Dual-Processing Accounts of Reasoning, Judgment, and Social Cognition," *Annual Review of Psychology*, 59(1), 255-78.

Glaser, M., T. Langer, and M. Weber (2013), "True Overconfidence in Interval Estimates: Evidence Based on a New Measure of Miscalibration," *Journal of Behavioral Decision Making*, forthcoming.

Glaser, M. and M. Weber (2007), "Overconfidence and Trading Volume," *Geneva Risk and Insurance Review*, 32(1), 36.

Gneezy, U., A. Kapteyn, and J. Potters (2003), "Evaluation Periods and Asset Prices in a Market Experiment," *Journal of Finance*, 58(2), 821-38.

Gneezy, U. and J. Potters (1997), "An Experiment on Risk Taking and Evaluation Periods," *Quarterly Journal of Economics*, 112(2), 631-45.

Graham, J. R., C. R. Harvey, and H. Huang (2009), "Investor Competence, Trading Frequency, and Home Bias," *Management Science*, 55(7), 1094-106.

Greenwood, R. and A. Shleifer (2013), "Expectations of Returns and Expected Returns," *Review of Financial Studies*, forthcoming.

Grinblatt, M. and M. Keloharju (2009), "Sensation Seeking, Overconfidence, and Trading Activity," *Journal of Finance*, 64(2), 549-78.

Hair, J. F., R. E. Anderson, R. L. Tatham, and W. C. Black (1998), *Multivariate Data Analysis*. Upper Saddle River, New Jersey: Prentice Hall.

Harris, M. and A. Raviv (1993), "Differences of Opinions Make a Horse Race," *Review of Financial Studies*, 6(3), 473-506.

Hoffmann, A. O. I. and T. Post (2012), "How Return and Risk Experiences Shape Investor Beliefs and Preferences," *working paper (Maastricht University)*.

Hoffmann, A. O. I., T. Post, and J. M. E. Pennings (2013a), "How Investor Perceptions Drive Actual Trading and Risk-Taking Behavior," *Journal of Behavioral Finance*, forthcoming.

Hoffmann, A. O. I., T. Post, and J. M. E. Pennings (2013b), "Individual Investor Perceptions and Behavior During the Financial Crisis," *Journal of Banking and Finance*, 37(1), 60-74.

Hoffmann, A. O. I. and H. Shefrin (2013), "The High Cost of Technical Analysis and Speculation," *working paper (Maastricht University)*.

Jonsson, A.-C. and C. M. Allwood (2003), "Stability and Variability in the Realism of Confidence Judgments Over Time, Content Domain, and Gender," *Personality and Individual Differences*, 34(4), 559-74.

Kahneman, D. (2003), "Maps of Bounded Rationality: Psychology for Behavioral Economics," *American Economic Review*, 93(5), 449-89.

Kahneman, D. (2011), *Thinking, Fast and Slow*. New York: Farrar, Straus and Giroux.

Kaniel, R., G. Saar, and S. Titman (2008), "Individual Investor Trading and Stock Returns," *Journal of Finance*, 63(1), 273-310.

Kaplanski, G., H. Levy, C. Veld, and Y. V. Veld-Merkoulova (2013), "Do Happy People Make Optimistic Investors?," *Journal of Financial and Quantitative Analysis*, forthcoming.

Kapteyn, A. and F. Teppa (2011), "Subjective Measures of Risk Aversion, Fixed Costs, and Portfolio Choice," *Journal of Economic Psychology*, 32(4), 564-80.

Kaustia, M. and S. Knüpfer (2008), "Do Investors Overweight Personal Experience? Evidence from IPO Subscriptions," *Journal of Finance*, 63(6), 2679-702.

Korniotis, G. M. and A. Kumar (2011), "Do Older Investors Make Better Investment Decisions?," *Review of Economics and Statistics*, 93(1), 244-65.

Kyle, A. and F. A. Wang (1997), "Speculation duopoly with agreement to disagree: Can overconfidence survive the market test?," *Journal of Finance*, 52(5), 2073-90.

Looney, C. A. and A. M. Hardin (2009), "Decision Support for Retirement Portfolio Management: Overcoming Myopic Loss Aversion via Technology Design," *Management Science*, 55(10), 1688-703.

Malmendier, U. and S. Nagel (2011), "Depression Babies: Do Macroeconomic Experiences Affect Risk-Taking?," *Quarterly Journal of Economics*, 126(1), 373-416.

Merkle, C. (2013), "Financial Overconfidence Over Time - Foresight, Hindsight, and Insight of Investors," *working paper (Mannheim University)*.

Millward-Brown (2006), *The Retail Investor 2006: Developments in the Market of Retail Investors in the Netherlands*. Amsterdam, The Netherlands.

Moore, D. O. and P. J. Healy (2008), "The Trouble With Overconfidence," *Psychological Review*, 115(2), 502-17.

Netemeyer, R. G., W. O. Bearden, and S. Sharma (2003), *Scaling Procedures: Issues and Applications*. Thousand Oaks, California: Sage Publications.

Odean, T. (1998), "Volume, Volatility, Price, and Profit When All Traders Are above Average," *Journal of Finance*, 53(6), 1887-934.

Odean, T. (1999), "Do Investors Trade Too Much?," *American Economic Review*, 89(5), 1279-97.

Parker, A. M. and B. Fischhoff (2005), "Decision-Making Competence: External Validation Through an Individual-Differences Approach," *Journal of Behavioral Decision Making*, 18(1), 1-27.

Pennings, J. M. E. and A. Smidts (2000), "Assessing the Construct Validity of Risk Attitude," *Management Science*, 46(10), 1337-48.

Pennings, J. M. E. and B. Wansink (2004), "Channel Contract Behavior: The Role of Risk Attitudes, Risk Perceptions, And Channel Members' Market Structures," *Journal of Business*, 77(4), 697-723.

Rouwendal, J. (2007), "Mortgage interest deductibility and homeownership in the Netherlands," *Journal of Housing and the Build Environment*, 22(4), 369-82.

Schultz, P. (2003), "Pseudo Market Timing and the Long-Run Underperformance of IPOs," *Journal of Finance*, 58(2), 483-518.

Seasholes, M. and N. Shu (2010), "Individual Investors and Local Bias," *Journal of Finance*, 65(5), 1987-2010.

Stanovich, K. E. and R. F. West (2000), "Individual Differences in Reasoning: Implications for the Rationality Debate? " *Behavioral and Brain Sciences*, 23(5), 645-65.

Statman, M., S. Thorley, and K. Vorkink (2006), "Investor Overconfidence and Trading Volume," *Review of Financial Studies*, 19(4), 1531-65.

van Rooij, M., A. Lusardi, and R. Alessie (2011), "Financial Literacy and Stock Market Participation," *Journal of Financial Economics*, 101(2), 449-72.

Varian, H. R. (1989), "Differences of Opinion in Financial Markets," in *Financial Risk: Theory, Evidence, and Implications*, C. C. Stone, ed. Boston, MA: Kluwer Academic Publishers, 3-40.

von Gaudecker, H.-M., A. van Soest, and E. Wengstroem (2011), "Heterogeneity in Risky Choice Behavior in a Broad Population," *American Economic Review*, 101(2), 664-94.

Walther, T. (2013), "The Information Acquisition Process of Individual Investors," *working paper (University of Munich)*.

Wärneryd, K.-E. (1996), "Risk Attitudes and Risky Behavior," *Journal of Economic Psychology*, 17(6), 749-70.

Weber, M., E. U. Weber, and A. Nosic (2013), "Who Takes Risks When and Why: Determinants of Changes in Investor Risk Taking," *Review of Finance*, 17(3), 847-83.

Windschitl, P. D. and G. L. Wells (1996), "Measuring Psychological Uncertainty: Verbal Versus Numeric Methods," *Journal of Experimental Psychology*, 2(4), 343-64.

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 his or 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).
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 Tolerance	Reflects a respondent's general predisposition toward financial risk. 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.
Confidence	Reflects a respondent's confidence about the response to the return expectation question. 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
Confidence	mean	5.31	5.35	5.45	5.48	5.40	5.58	5.62	5.48	5.42	5.32	5.51	5.38
	std	0.96	0.96	0.94	0.99	1.07	1.00	0.97	1.04	1.03	1.06	0.98	1.04

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 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)
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)
Confidence (1 = low confidence, 7 = high confidence)	
How confident are you about this answer? †	1 (not confident at all)–7 (very confident)

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 tolerance, risk perception, confidence) is calculated as the equally weighted average of the respective survey questions. * denotes a reverse-scored question. † indicates that this question is asked five times, that is, after each return expectation question.

Table 4

One-Month Transition Matrix Across Deciles of Confidence Distribution

Decile t-1	Decile t (Percentages)									
	1	2	3	4	5	6	7	8	9	10
1	35.9	21.0	11.0	10.8	6.2	4.4	3.6	3.3	2.6	1.3
2	18.6	25.0	21.0	12.2	9.0	5.9	2.9	2.7	1.9	0.8
3	14.4	18.5	17.0	13.9	13.2	7.4	7.7	5.0	1.4	1.4
4	6.9	12.0	17.4	18.9	14.0	12.5	8.9	5.9	1.8	1.8
5	7.5	8.7	13.9	16.2	15.4	13.4	11.6	8.2	3.6	1.5
6	4.2	3.2	11.0	11.7	14.9	21.1	13.9	9.7	6.2	4.0
7	4.0	3.8	6.1	8.9	9.6	14.6	22.5	15.3	10.3	4.9
8	1.3	3.2	4.2	5.0	7.9	11.6	20.2	20.2	17.9	8.7
9	2.2	2.2	2.5	2.0	4.7	6.5	11.2	16.4	25.6	26.6
10	1.7	1.2	1.7	1.7	1.7	1.9	5.5	6.9	24.9	52.9

This table presents transition probabilities for an investor moving from a particular decile in the distribution of confidence at the end of the previous month to a decile in the corresponding distribution at the end of the current month. The confidence measure is defined in Table 1.

Table 5
Impact of Past Return and Confidence on Changes in Return Expectation

Dependent Variable	Δ Return Expectation			Δ Return Expectation			Δ Return Expectation		
	Coef.	Std. err.		Coef.	Std. err.		Coef.	Std. err.	
Return	0.423	0.086	***	-0.461	0.432		0.349	0.102	***
Confidence t-1				0.032	0.014	**			
Return*Confidence t-1				0.159	0.075	**			
Mean Confidence > 75%							0.010	0.027	
Return*Mean Confidence > 75%							0.259	0.156	*
Gender	0.054	0.039		0.053	0.040		0.060	0.040	
Age	0.000	0.001		0.000	0.001		0.000	0.001	
Account Tenure	-0.002	0.003		-0.002	0.003		-0.002	0.003	
ln(Income)	0.025	0.088		0.026	0.088		0.020	0.088	
ln(Avg. Portfolio Value)	-0.003	0.006		-0.003	0.006		-0.003	0.006	
ln(House Value)	0.013	0.045		0.012	0.045		0.016	0.045	
Derivatives	0.049	0.036		0.052	0.036		0.050	0.036	
Constant	-0.650	0.586		-0.067	0.590		-0.646	0.585	
Time fixed effects	YES			YES			YES		
N Observations	3,955			3,955			3,955		
N Investors	1,045			1,045			1,045		
R^2	0.164			0.165			0.164		

This table presents the results from regressions of changes in investor return expectations (= Return Expectation$_t$ – Return Expectation$_{t-1}$) on past investor returns (column 1), continuous (column 2) or discrete (column 3) interactions of past returns with past confidence, and a set of control variables. That is, we regress the monthly update of return expectations 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 Confidence on Absolute Changes in Return Expectations

Dependent Variable	ABS[Δ Return Expectation]			ABS[Δ Return Expectation]		
	Coef.	Std. err.		Coef.	Std. err.	
Confidence Prev. Month	0.092	0.012	***	0.092	0.012	***
Std(Return)				0.044	0.047	
Gender	-0.033	0.040		-0.032	0.040	
Age	0.002	0.001	**	0.002	0.001	**
Account Tenure	-0.005	0.005		-0.005	0.005	
ln(Income)	0.051	0.118		0.049	0.119	
ln(Avg. Portfolio Value)	0.011	0.008		0.013	0.008	
ln(House Value)	-0.008	0.057		-0.007	0.057	
Derivatives	0.035	0.033		0.026	0.034	
Constant	-0.368	0.803		-0.387	0.804	
Time fixed effects	YES			YES		
N Observations	3,955			3,955		
N Investors	1,045			1,045		
R^2	0.046			0.047		

This table presents the results from regressions of absolute value of changes in investor return expectations (= ABS[Return Expectation$_t$ – Return Expectation$_{t-1}$]) on past confidence and a set of control variables. 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 Absolute Changes in Return Expectations on Turnover

Dependent Variable	Turnover			Turnover		
	Coef.	Std. err.		Coef.	Std. err.	
ABS[Δ Return Expectation] t-1	0.070	0.028	**	0.071	0.028	**
Risk Tolerance t-1				0.030	0.024	
Risk Perception t-1				0.033	0.017	*
Gender	-0.084	0.067		-0.075	0.066	
Age	0.001	0.003		0.002	0.003	
Account Tenure	0.009	0.009		0.008	0.009	
ln(Income)	0.224	0.241		0.203	0.240	
ln(Avg. Portfolio Value)	-0.083	0.023	***	-0.084	0.023	***
ln(House Value)	-0.238	0.139	*	-0.226	0.139	
Derivatives	0.053	0.048		0.061	0.048	
Constant	1.546	1.501		1.336	1.455	
Time fixed effects	YES			YES		
N Observations	1,369			1,369		
N Investors	523			523		
R^2	0.083			0.089		

This table presents the results from regressions of turnover on the lagged absolute value of changes in investor return expectations (= ABS[Return Expectation$_{t-1}$ – Return Expectation$_{t-2}$]) and a set of control variables. The columns show results of linear panel models. The number of individual investors included in the regression (523) is smaller than in the previous regressions (1,045), because the sample refers to investors that traded in a particular month and because the use of lagged absolute changes in return expectation reduces the panel length. 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 8

Heterogeneity in Return Experiences and Changes in Return Expectations

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
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
Return	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
Fraction Return >= 0		0.77	0.65	0.03	0.16	0.85	0.02	0.16	0.16	0.41	0.61	0.07	0.62
Δ Return Expectation	mean		-0.11	-0.60	0.20	0.32	-0.65	-0.08	0.22	0.13	0.25	-0.43	0.63
Δ Return Expectation	sd		0.92	0.97	0.90	0.84	0.97	0.88	0.91	0.89	0.88	0.96	0.93
Fraction Δ Return Expectation >=0			0.47	0.23	0.56	0.67	0.23	0.38	0.61	0.50	0.60	0.31	0.72
ABS[Δ Return Expectation]	mean		0.69	0.90	0.67	0.69	0.92	0.69	0.72	0.65	0.68	0.79	0.83
ABS[Δ Return Expectation]	sd		0.61	0.69	0.63	0.56	0.73	0.59	0.60	0.62	0.61	0.69	0.74

This table presents monthly summary statistics for investor returns, changes in return expectations, and absolute changes in return expectations. Variables are defined in Table 1.

Table 9

Impact of Past Return Expectations and Confidence on Return Performance

Dependent Variable	Return			Return			Return		
	Coef.	Std. err.		Coef.	Std. err.		Coef.	Std. err.	
Return Expectation t-1	0.003	0.003		0.012	0.017				
Confidence t-1				0.001	0.012		-0.007	0.004	*
Return Expectation t-1*Confidence t-1				-0.002	0.003				
Gender	0.006	0.009		0.007	0.009		0.006	0.010	
Age	0.000	0.000		0.000	0.000		0.000	0.000	
Account Tenure	0.000	0.001		0.000	0.001		0.000	0.001	
ln(Income)	0.000	0.028		-0.002	0.028		-0.009	0.029	
ln(Avg. Portfolio Value)	0.016	0.003	***	0.016	0.003	***	0.017	0.003	***
ln(House Value)	0.010	0.016		0.010	0.016		0.012	0.017	
Derivatives	-0.079	0.013	***	-0.079	0.013	***	-0.099	0.013	***
Traded	-0.015	0.006	**	-0.015	0.006	**			
Turnover	-0.014	0.003	***	-0.014	0.003	***			
Constant	-0.365	0.230		-0.361	0.233		-0.296	0.238	
Time fixed effects	YES			YES			YES		
N Observations	3,955			3,955			3,955		
N Investors	1,045			1,045			1,045		
R^2	0.323			0.324			0.295		

This table presents the results from regressions of investors' returns on past investor expectations (column 1), continuous interactions of past returns with past confidence (column 2), past confidence (column 3), and a set of control variables. 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 10

Relation between Confidence and Portfolio Risk

Dependent Variable	Std(Return)		
	Coef.	Std. err.	
Confidence Prev. Month	0.015	0.007	**
Return Expectation t-1	-0.003	0.008	
Risk Perception t-1	0.014	0.004	***
Risk Tolerance t-1	0.023	0.007	***
Gender	-0.024	0.024	
Age	0.000	0.001	
Account Tenure	0.008	0.003	**
ln(Income)	0.048	0.059	
ln(Avg. Portfolio Value)	-0.052	0.008	***
ln(House Value)	-0.005	0.035	
Derivatives	0.208	0.029	***
Constant	0.187	0.403	
Time fixed effects	YES		
N Observations	3,955		
N Investors	1,045		
R^2	0.277		

This table presents the results from the regression of investors' portfolio risk (standard deviation) on past investor confidence, beliefs and preferences, and a set of control variables. The column shows results of a linear panel model. 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.

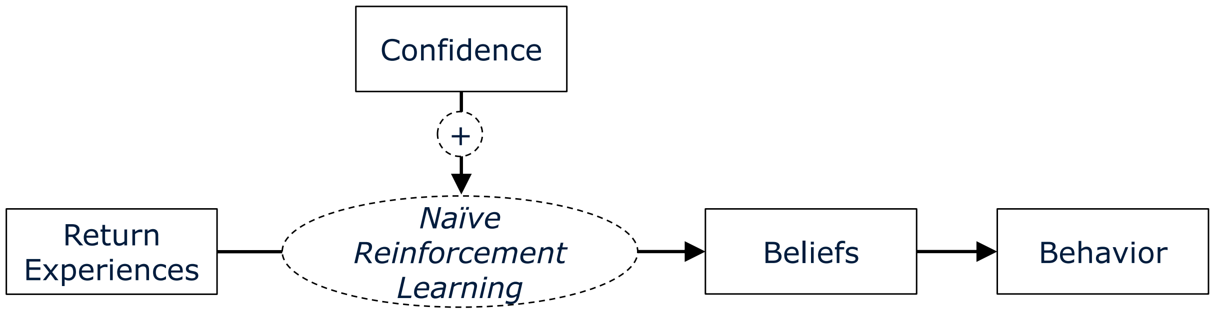

Figure 1. Theoretical Framework.

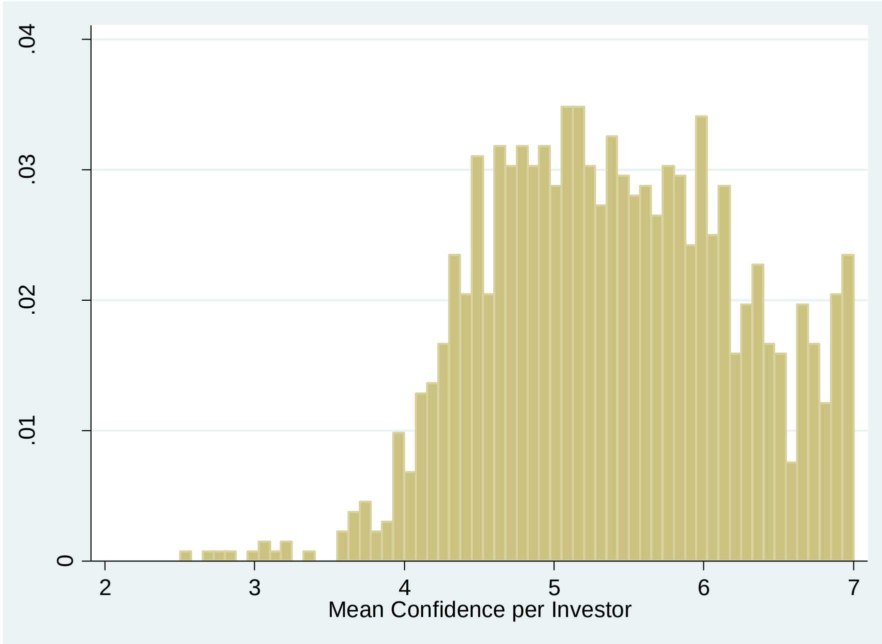

Figure 2. Distribution of Mean Investor Confidence. Mean confidence is the mean calculated over all observations per investor (time-series mean). Confidence is measured on a 7-point Likert scale (see Table 3). A small value indicates low confidence, whereas a large value indicates high confidence.

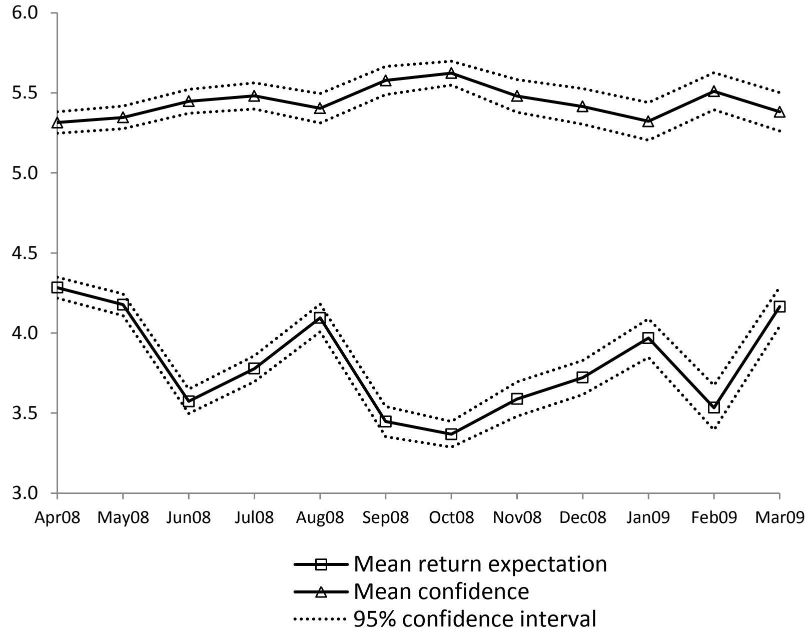

Figure 3. Investor Return Expectations and Confidence. Return expectations and confidence are measured on a 7-point Likert scale (see Table 3). A small value indicates low return expectations or confidence, whereas a large value indicates high return expectations or confidence.

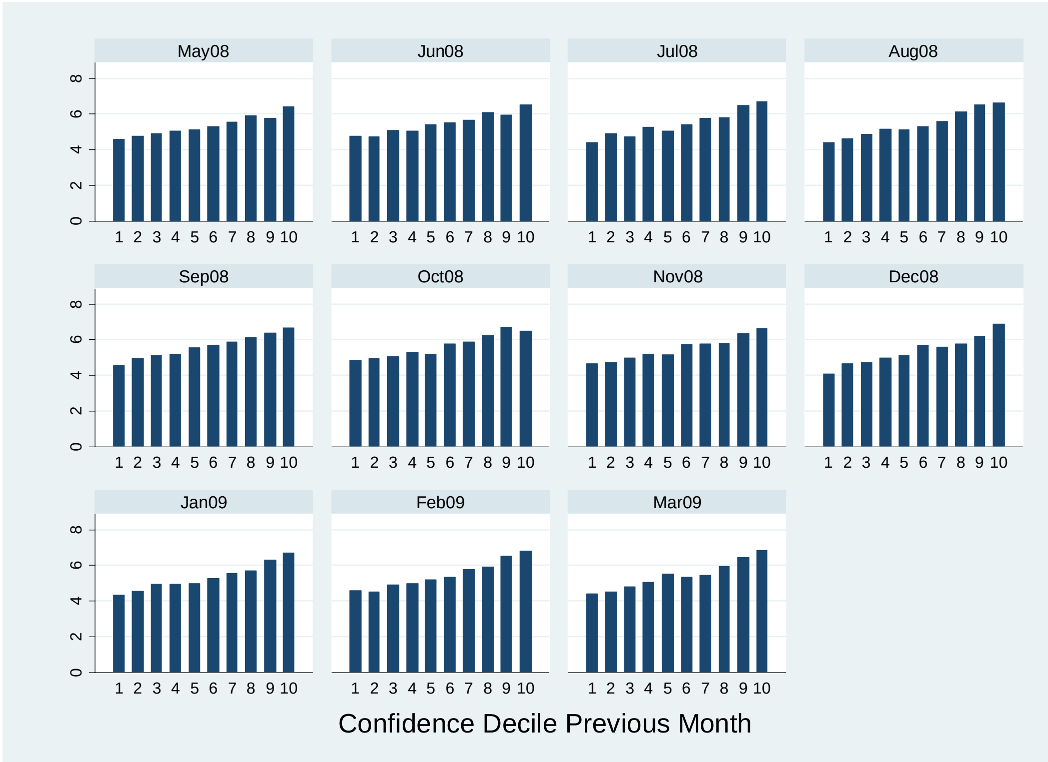

Figure 4. Mean of Investor Current Confidence per Confidence Decile Previous Month. This figure shows the mean confidence of investors at the end of a particular month per decile of the distribution of confidence of the previous month (cross-sectional mean). Confidence is measured on a 7-point Likert scale (see Table 3). A small value indicates low confidence, whereas a large value indicates high confidence.

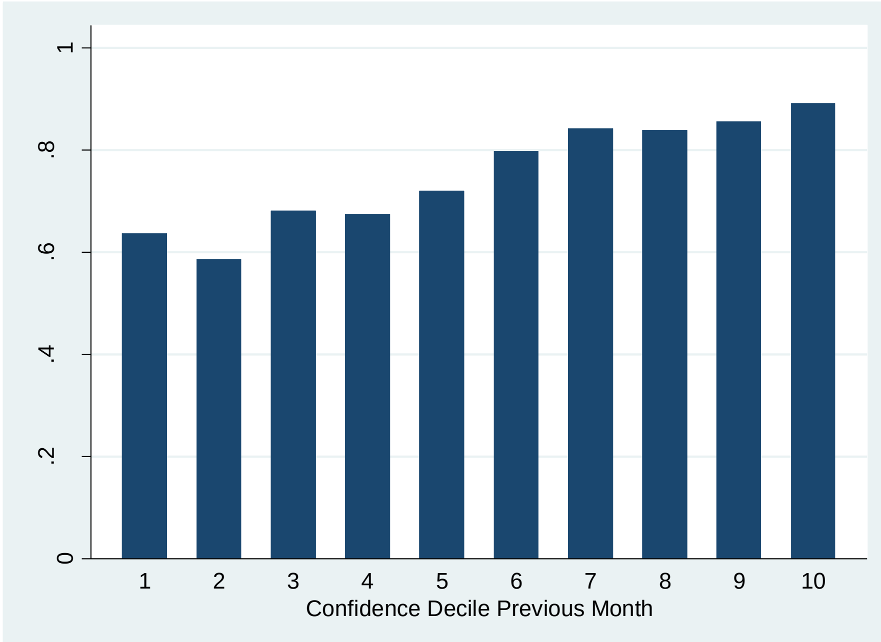

Figure 5. Mean of Absolute Changes in Return Expectations per Confidence Decile Previous Month. This figure shows the mean absolute change of investor return expectations (= mean of ABS[Return Expectation$_t$ – Return Expectation$_{t-1}$]) per decile of the distribution of confidence of the previous month. Return expectation and confidence are measured on a 7-point Likert scale (see Table 3). A small value indicates low return expectation or confidence, whereas a large value indicates high return expectation or confidence.